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Development of a Management Zone Scoring Index & Economic Returns of Grid & Management Zone Soil Sampling in Coastal Plain Soils of the Southeastern United States

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DEVELOPMENT OF A MANAGEMENT ZONE SCORING INDEX & ECONOMIC RETURNS OF GRID & MANAGEMENT ZONE SOIL SAMPLING IN COASTAL PLAIN SOILS OF THE SOUTHEASTERN UNITED STATES

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ABSTRACT

Precision agriculture seeks to improve conventional farming practices through the use of Management Zones (MZ). There are many ways to create MZs and it's not always easy to decide which MZ would provide optimal results for the specified application. Good MZs should have little variation within a zone, but large differences when compared to other zones. Previous research has been inconsistent on the ability of MZs to capture yield variation. One objective of this research was the development and application of the Management Zone Scoring Index (MZSI) to assess efficacy of 13 zone delineation methods at capturing yield data variation. The score was calculated by quantifying the variation of yield data between MZs and dividing this by the variation of yield data within a MZ. This scoring method was applied to 204 MZ's created using soil and yield data ranging from 2006-2017. Significant differences were observed ($F_{169,12}$=4.045, p<0.0001). The top statistical grouping consisted of: same-crop composite yield maps (0.964), different-crop composite yield maps (0.723), 1 year same-crop yield maps (0.680), shallow EC divided by deep EC (0.620), and shallow EC (0.595). By creating a scoring system to evaluate how well each MZ delineation method captures the spatial variability of yield, growers and consultants can make better decisions on how to develop MZs for application of site-specific management to benefit their operation.

No previous research was found that defined the Economically Optimum Grid Sampling Size (EOGSS) (Lawrence, 2019). Additional objectives of this research were to: 1) determine the Cost of Sub-Optimal Management (CSM) for 14 soil sampling strategies;

2) determine an economically optimum grid sampling size (EOGSS); and 3) evaluate how accurately each MZ delineation method captures the spatial variability of phosphorus, potassium, and pH. Two hundred and four hectares in the coastal plain region of South Carolina were soil sampled using grid sizes of 0.4, 0.49, or 0.61 ha. Composites of these samples were combined to simulate larger grid sampling. Within the assumptions of this study, an EOGSS in cotton production was determined to be 0.43 ha. Sand content was found to be the most profitable MZ delineation with a CSM of \$304 ha^{-1}. Whole field or uniform management was the worst performing zone classification method with a CSM of \$387 ha^{-1}. While the analyses and data presented here may not be explicitly relevant to regions, fields, and crops not represented, this study presents a methodology for determination of the EOGSS and CSM of grid and zone soil sampling. By using methods described here, growers and consultants can be informed about methods to improve management practices, maximize economic returns from variable rate nutrient applications, and reduce environmental impacts from nutrient applications.

Dedication

I would like to dedicate this paper to my wife who was always very supportive of me and was willing to make sacrifices if necessary to help me pursue this degree. Also I would like to dedicate this paper to my parents who instilled in the drive to succeed and advance in life. I am who I am because of my upbringing and I believe they did a great job.

Acknowledgements

I would like to acknowledge Dr. Kendall Kirk for always being available to guide me through any problems that may have arisen and for providing both the yield data and connections to growers in order to obtain further yield data needed for this project.

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Additionally, I would like to acknowledge Kayla Carroll who assisted me in collecting hundreds soil samples and diligently performed the soil texture analysis.

The precision agriculture crew at Clemson University's Edisto Research & Education Center deserve a big acknowledgment for collection of several crucial datasets for this project and many others. They spent many hours scattered across fields for the benefit of agriculture

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LIST OF ABBREVIATIONS

MZ..............................management zone

CSM...........................cost of suboptimal management

EOGSS.......................economically optimum grid sampling size

EC ....electrical conductivity

DAP............................diammonium phosphate

MOP...........................muriate of potash

PA...............................precision agriculture

SSURGO....................USDA soil survey geographic database

NDVI..........................normalized difference vegetation index

SID ....spatial image digitizer

PPMU.........................point polygon merge utility

USDA.........................United States Department of Agriculture

CHAPTER 1. INTRODUCTION

Precision agriculture seeks to improve conventional farming practices through the use of Management Zones (MZ), which divide a field into smaller areas based on spatially unique characteristics. Field variability must be defined and measured in order to classify areas of fields into MZs. Within the last decade, sensing technology in agriculture has allowed field data to be generated at an increased scale. With yield monitors becoming standard equipment, growers are accumulating valuable data on their operation. Additionally, technologies such as near real-time, satellite and drone imagery, soil Electrical Conductivity (EC), on-the-go organic matter sensors, and the USDA Web Soil Survey all provide various spatially descriptive field data.

Management zones can be developed from these data layers or combinations of datasets. Management zones based on yield, which is what this study focuses on, is only one application of MZs. Additionally, MZs can be applied to various, specific objectives. For example when planting corn in a partially irrigated field, a grower may reduce the planting population when planting an area outside of irrigation boundaries; or, when applying a fumigant to reduce the population of soil-borne pests such as nematodes, the rate of fumigant could be altered based on a characteristic that is believed to relate to the pest population such as sand content. The objective of the MZ will influence which data sets are chosen to create the MZ from. Soil fertility sampling and subsequent fertilizer application are activities that can greatly benefit from the implementation of MZs (Nawar, 2017). A commonly used method of creating management zones is grid sampling. Grid sampling is the process of dividing a whole field into equal sized areas where sampling can then take place. Accurately capturing the variability in soil fertility across a field should optimize prescription of fertilizer rate and placement which should subsequently maximize yield potential relative to fertilizer needs. Larger grid areas provide reduced resolution of the actual variability within the field, however, sampling costs and analysis are concurrently reduced. Small grids provide more precise analysis of fertility needs. With small grids greater sampling and analysis costs occur due to the increased number of samples collected and processed. In order to increase sampling efficiency, zone management is often utilized to divide the field into homogenous areas based on geospatial data acquired from one or more sources. Typically, when soil sampling, one composite soil fertility sample is collected from each zone. Composite samples from a field equal the number of zones defined in the field.

Fertilizer and lime costs make up approximately 20% of the total production cost of cotton (Clemson University, 2017), therefore making these inputs important relative to profitability. Depending on the size and basis used for zone development, zones can vary in how effective they are at adequately describing and classifying the variability of the field into homogenous regions. Soil fertility sampling is often the first activity done in preparation for the growing season. Therefore, it is the foundation on which the rest of the crop production year is based. There is limited research comparing the economics of grid and zone management (Nawar, 2017; Lawrence, 2019).

An objective of this study was to compare thirteen methods of delineating MZs to determine which method is the most suitable for capturing in-field variability of yield. The goal of any successful MZ strategy is to take a heterogeneous field and divide it into smaller homogenous sections that specifically relate to the practice for which the zones will be used, for example planting or fertilizing. If developed correctly there should be small variations in the value of a given characteristic within each zone. However, this value should possess characteristics different enough from other MZs to merit creation of a separate zone. To evaluate these differences, a scoring system was developed and applied in this study to evaluate thirteen MZ delineation methods to generate higher scores when differences within a zone are minimized and differences between zones are maximized.

Additionally, this research developed and applied a method for comparing economic returns associated with fourteen MZs and 9 grid sizes, whereby the CSM is representative of the costs incurred by not having optimal management pertaining to fertilization in cotton production. A theoretical CSM of $0, not considering sampling and analysis costs, would mean that at every point in the field the fertilizer needs were precisely met with no over- or under-application and lime application rate and placement for managing pH was precisely correct. The CSM was then used to estimate an EOGSS for grid sampling. The development and implementation of the zone scoring system and the CSM comparison methodology will allow growers and consultants to be better educated on how different MZs affect their operation and which MZ delineation method may benefit them the most.

CHAPTER 2. DEVELOPMENT AND APPLICATION OF A MANAGEMENT ZONE SCORING SYSTEM

INTRODUCTION

The concept of dividing a large field into smaller management areas based on its characteristics and the spatial distribution of these characteristics is the foundation of PA. Advancements in agricultural sensor technology has allowed field data to be gathered at an increased scale. Yield monitors, being one of the most widely adopted PA technologies, are allowing growers to make inferences on why certain areas of a field yield better than others. Additionally, technologies for geospatial data such as current satellite or drone imagery, soil electrical conductivity (EC), and USDA Web Soil Survey all provide valuable field data. There are numerous characteristics that can be quantified, mapped, and used to create MZs, many of which being quantifiable using remote sensing technologies. However, there is limited conclusive research comparing multiple MZ strategies. Growers have access to several datasets to create MZs, but it is not always clear which dataset provides optimal results. One goal of this study is to introduce a scoring system as a methodology for comparing strategies and field data used for MZ delineation. The system developed suggests which method is the most suitable for capturing in-field variability by maximizing the difference between management zones but minimizing within zone variation.

Impacts of precision agriculture on production agriculture

A goal of site-specific management is to increase profitability while reducing environmental impacts by capitalizing on more precisely managing the inherent spatial differences across every field. PA technologies have become more readily available in the past two decades and the average size of production agriculture farms has increased while the number of midsize production agriculture farms has decreased (James, 2013). From 1982 to 2007 the midpoint acreage of production agriculture farms has almost doubled from 238 ha to 447 ha. Larger farms (>1537 ha) have proven to provide better financial stability and more efficiently utilize capital and labor (Schimmelpfennig, 2016). This allows larger farms to mitigate the upfront capital investment cost because the payback period is a function of area. Also larger and more successful farms, like in any business, tend to be more progressively managed and thus would be more apt to adopt new technology. The largest farms (>1537 ha) have double the precision agriculture adoption rate compared to all other farm sizes (Schimmelpfennig, 2016). The largest farms, those consisting of more than 3,800 acres, have an adoption rate of around 80% for GPS soil/yield mapping and guidance systems. At the same time, for the same group, the adoption rate for variable rate technologies is only 40% (Schimmelpfennig, 2016).

A major factor in adoption of PA technologies is the profit realized from reducing inputs and/or increasing yield. It's obvious that not all growers are convinced that variable rate technology will benefit them enough to justify the initial investment cost. If they were, the adoption rates would be much higher (Pringle, 2003). A study on the long-term impact of PA management systems was conducted by at the University of Missouri spanning twenty years (Yost, 2017). The first ten years (1993-2003), the field was managed conventionally with normal tillage and all inputs being applied at a uniform rate. From 2004-2014 a PA management system was established that included 30 m grid sampling, variable rate nitrogen fertilization based on crop reflectance, and variable rate phosphorus, potassium, and lime applications based on soil tests. Cover crops were established, and no-till management was adopted. After 10 years of PA management, grain yield, relative to normal yields, had not changed but temporal yield variation was reduced by 30% (Yost, 2017). In 2019 an economic analysis was conducted from this study and it found that the PA system reduced tillage and pesticide costs but increased fertilizer, cover crop, and seed expenses. Overall, the PA system increased cost per hectare by $97. This is without any subsidies available for planting cover crops or performing better environmental practices. However, the only statistical differences in profitability between the two systems occurred in a drainage channel that occupied 3% of the field. In this normally wet area, no-till practices along with cover crop residue made it difficult to establish the cash crop and resulted in statistically lower profits (Yost, 2019). Return on investment from PA technologies has been demonstrated to vary. These results may not be representative of the results of others in different localities. Although this research did not demonstrate substantial profit gains from PA technologies, it showed that they can maintain profits while allowing farmers to practice more sustainable crop production methods.

Conversely, Nawar et al. concluded, from observing several studies, that farm production efficiency generally increased with the implementation of variable rate fertilizer application guided by MZs compared to uniform rate management. This increase in efficiency often lead to reduced environmental impacts as well. The amount of field variability will directly affect how easily PA technologies are implemented. A large degree of variability will inherently generate better responses to PA implementation. PA practices have the potential to be beneficial agronomically, environmentally, and financially but profitability is the number one driver for adoption of PA technology. Studies that show how

PA technology can financially benefit a grower in a commercial environment are limited (Nawar, 2017).

Technologies associated with soil-based management zone delineation

Soil samples are the foundation on which most variable rate fertilizer prescriptions are based. How and where the samples are collected defines the zone delineation method. The simplest method for capturing the spatial variability of soil properties is grid sampling or taking samples from equal area grids across a field. Grid sampling can be likened to pixels in a picture. When variation is present, large grids give less resolution of the field variability, but the sampling cost is lower. Small grids give better resolution but with higher sampling and laboratory analysis costs because the number of samples is higher.

Another method for characterizing variability in soil fertility is using zones created from areas with similar soil properties or similar yield potential. There are several ways to create zones, and inherently some zone criteria are more effective than others in classifying the actual in-field variability as related to yield and/or fertility needs. Perhaps the easiest and least expensive zone delineation method for a farmer to implement is with the use of the United States Department of Agriculture (USDA) soil survey geographic database (SSURGO). This was a broad soil survey done by the USDA Natural Resources Conservation Service (NRCS). At no cost, MZs can be created in an area of interest without setting foot in the field in a matter of minutes. However, SSURGO maps were not designed to be used for precision agriculture but instead were meant to be a geologic survey to create an inventory the soils by county and state. Ferhatoglu et al. (2019) compared utilizing the USDA Web Soil Survey to four other zone delineation methods from fifteen fields in

Illinois and North Carolina. These methods were: 1). two years of monthly satellite imagery; 2). only satellite imagery with uniform management; 3). normalized difference vegetation index (NDVI); and 4) a control, randomly created polygons. They found using the Web Soil Survey to be equal to or worse than their control in all of their fields. Two years of monthly satellite imagery was found to be the best predictor of soil variability. They evaluated the MZ created by comparing the variance of the mean soil parameters both across and within MZs and by quantifying the number of significant zone divisions that prescribed a fertilizer rate large enough to warrant agronomic importance.

Another method for delineating MZs is by elevation or topography in a field. This can also be done at little to no cost without visiting the field via satellite imagery or with any GPS receiver with logging capabilities mounted on a tractor or other vehicle. Elevation data is readily available through yield maps or guidance systems. However, growers should know what correction source they are using. Less expensive systems may use the Wide Area Augmentation System (WAAS) which has an elevation accuracy of not more than 7.6 m (FAA, 2001). This system may be used on equipment conducting less precise activities such as tillage or spreading. Real time kinematic (RTK), the correction service used for most auto-steer applications, has an elevation accuracy of 5 cm or less (Ag Leader, 2011). Fraisse et al. (2001) determined that topography based MZs are a valuable method for capturing in-field variability, especially for clay-pan soils, and indicated that topography relates to plant water availability.

Soil EC is another soil-based method used for delineating MZs. Unlike elevation or SSURGO, collecting soil EC data requires a dedicated trip across the field with a device that measures the electrical resistance of the soil. Soil EC, being an inverse measurement of electrical resistance, correlates well with soil texture, water holding capacity, salinity, and many other factors that would affect conductivity. Neely et al. (2016) determined that soil EC mainly correlated to soil texture and moisture content. Jaynes et al. (2005) discovered that Soil EC and elevation could correctly predict 5-year high and low yielding areas 80% of the time in soybeans. Guo et al. (2012) correlated soil EC, bare soil imagery, and elevation to cotton yields over 5 years. Deep EC (0-90cm) had a stronger correlation to cotton yield than shallow EC (0-30cm). Also the correlation was stronger in relatively dry years compared to years with higher rainfall. Elevation was found to not be as valuable as EC or bare soil imagery.

The last technology evaluated in this study is a software program called Spatial Image Digitizer (SID) (Kirk, 2016). Spatial image digitizer is designed to take an image, geo-reference it, and extract the pixel color information from within a field boundary. Pixel color information contains: red, green, and blue color values along with brightness. Bare soil imagery has been in use in PA for a long time but only recently has the ability to digitize it and create a map directly came into fruition. Once the pixel color and brightness information has been extracted, it can then be exported as tabulated map data in the form of a comma separated values (CSV) file to be loaded into a GIS data management program to create MZs. Hornung et al. (2006) compared a soil color based MZ delineation method to a yield-based MZ delineation method and found that the soil color method outperformed the yield-based method at more accurately capturing the yield potential variability within the field. The soil-based method consisted of tilled bare soil imagery, elevation, and farmer experience while the yield-based method consisted of multispectral imagery of bare soil, soil organic matter, soil cation exchange capacity, soil texture, and the yield map from the previous year. It was found at three site years, using several decision methodologies, that the soil-based method more accurately captured the yield potential variability within the field.

Technologies associated with yield-based management zone delineation

Yield is the sum of all the variables that affect crop growth throughout a given growing season. Schepers et al. (2004) demonstrated that MZs based solely on soil properties do not always account for all of the temporal variability that affects yield, even under irrigation. In 2010, 70% of corn farmland utilized yield monitors but only 44% of corn farmland utilized yield maps (Schimmelpfennig, 2016). Many growers have yield monitors but do not fully utilize the data they already have. Maestrini et al. (2018) amassed yield data and multispectral imagery from multiple years on 571 fields across the Midwest in order to evaluate the best predictor of spatial yield variability. Historical yield data, calculated from at least four years of normalized different-crop yield data, was compared to the multispectral red band, NDVI, and canopy temperature. Historical yield data proved to be the best predictor in areas with low temporal variability and in-season NDVI imagery was the best in areas with high temporal variability.

One of the drawbacks of using yield data to generate MZs is that many growers have 2- or 3-year crop rotations in their fields. In order to account for temporal variability, multiple years of crop yield data are needed to determine which areas of a field are consistently higher yielding than others. For example, if a farmer is on a corn-soybean-cotton rotation then it will take 9 years before that grower has 3 years of yield data from any one crop. Brock et al. (2005) analyzed the viability of using different-crop yield data in a corn-soybean rotation to capture yield variability. They compared soil-based MZs, yield-based MZs from both crops, and yield-based MZs from separate crops and found the latter to be the most accurate at capturing the yield variability in both crops.

OBJECTIVES

The objectives of this study were to: (1) develop a scoring system for evaluating the suitability of various MZ development methodologies for classifying yield potential and (2) demonstrate application of the scoring system for comparing selected MZ development methodologies.

MATERIALS & METHODS

Yield and soil data for this study was collected from five farms throughout the coastal plains region of South Carolina and Georgia. Yield data ranged from 2006 through 2017 and was limited to cotton and corn. Data was organized by recording farm name, field name, year, crop, acreage, and irrigation status. All yield datasets were filtered using Yield Doctor (Kirk, 2018), which filters yield data by calculating the inter-quartile range (IQR) of the grain mass flow sensor output, ground speed, yield, and moisture content. Any data that lies outside +/- 1.5 IQR was removed from the dataset. Yield monitor data inherently contains many errors that need to be removed to ensure data integrity (Ping & Dobermann, 2005). This was done to delete any erroneous data points the yield monitor may record and generally removed less than 10% of the total data points.

Soil data was also collected where available. This included Shallow EC, Deep EC, Average EC, Elevation, USDA SSURGO (SSURGO), bare soil imagery pixel brightness (SID Brightness), and bare soil imagery blue color value (SID Blue). Soil EC data was collected with a Veris 3100 soil EC meter (Veris Technologies, Inc., Salina, Kans.) which has coulters that makes contact with the soil and sends an electrical current through the soil from one coulter to another. Resistance to the electrical current is measured, converted to a measurement of conductivity, and recorded along with position data obtained from an onboard GPS receiver. The Veris 3100 provides three measurements of soil EC: shallow (0-30 cm), deep (0-90 cm), and an average of the two. Depending on model and coulter spacing, specific depth ranges can vary. Additionally, from this data two other, calculated datasets were created. It was hypothesized that a ratio between the shallow and deep EC values was worth investigation so shallow was divided by deep to achieve this (ShEC/DpEC). This data will provide a difference map of the topsoil to subsoil. True Deep EC represents a calculated EC for the 30-90 cm depth and was calculated as a reverse weighted average of deep EC, where deep EC is assumed to represent the weighted average of shallow EC and true deep EC:

$$True\ Deep\ EC = \frac{90 \cdot Deep\ EC - 30 \cdot Shallow\ EC}{60} \tag{1}$$

Elevation data is recorded by the yield monitor during harvest so all elevation data was sourced from the yield data. Bare soil imagery was collected through satellite imagery sources where available. Care was taken to only select images that showed bare soil conditions. Presence of cloud cover, poor image resolution, shadowing, plant growth, and heavy plant residue were all used to disqualify an image from being used. Spatial image digitizer software was used to obtain pixel brightness (SID BRT) and blue color space value (SID Blue) from the aerial images.

All tabulated, point datasets discussed above were imported into Farmworks (Trimble Ag Software, Sunnyvale, CA). Field boundaries were created as polygons for every non-irrigated field by either tracing the edge of the field from satellite imagery or by tracing the edge of the yield data. Field boundaries for every irrigated field were created by tracing a circular polygon of the center pivot thereby only including irrigated data.

To compare how well the datasets performed at capturing in-field variability MZs had to be created from point data. Each year, yield data and every layer of soil data in each field had contour maps generated in Farmworks. To standardize the process, ranges for zone divisions were set at ½ standard deviation of each layer contoured. Farmworks software creates ½ standard deviation divisions by creating one range with a lower limit equal to ¼ standard deviation below the mean and an upper limit equal to ¼ standard deviation above the mean. Additional ranges are created above this range in ½ standard deviation increments. For yield data sets only, an extra contour map was generated with ranges for zone divisions set at four equal divisions of the data. These four equal division zones were used for comparison to the ½ standard deviation zones discussed above because ½ standard deviation often produced zones so small in size that they are not practical to implement PA practices such as variable rate application of fertilizer. Farmworks defines upper and lower limits of each range for the four equal range divisions by defining range limits at intervals such that each of the four ranges contain the same number of data points for a given layer.

Composite yield maps were created by normalizing yield data from at least two years and combining them together. This was completed in Yield Doctor by generating a 232 m^2 grid across the field, assigning a normalized yield value to each grid square, and then averaging each year's yield value for that grid square. Normalization, or standardization, of yield data in Yield Doctor for comparison across crops and years is accomplished by dividing yield for a given position by the average yield for the dataset; for example, a value for a given point of 1.1 would suggest that the yield at that point was 10% above the average yield for that crop year. These normalized yields for each year were used to create point datasets of multiyear, composite yield data. Composite yield data was created for several combinations of same-crop and different-crop combinations. For example, if a field had six years of yield data with three corn years and three cotton years, composite yield maps were created for: only corn, only cotton, and all data (corn and cotton combined). The yield maps were classified as either same-crop yield or different-crop yield. Composite yield maps were deemed as different-crop if there was at least one year of different-crop data.

For creation of the polygons representing the zones, contours were created in Farmworks using 15.24 m cell size, averaging method, fill blanks enabled, 0% smoothing, and a minimum area of 0 ac. An Esri (Esri, Redlands, Calif.) polygon type shape file (SHP) was then generated from the contour map with each zone named as average data layer value within the zone. The SHP files were exported and then imported to Point Polygon Merge Utility (PPMU) (Kirk, 2016). This program allows a point dataset in comma separated values format (CSV), such as filtered yield data, to be overlaid on top of a shape file format

(SHP) polygon dataset. The software determines the polygon, if any, in which each CSV point resides. After processing all points in the imported CSV file, PPMU creates a duplicate CSV file with an added column stating the user-specified attribute value for the polygon in which each point resides. All yield (point) datasets were processed in this manner for all developed polygon SHP files representing the zone methods.

The polygon appended point data was then imported into JMP statistical software (SAS Institute, Cary, NC) for calculation of the standard deviation and mean values from each zone. These summaries, for each yield x zone map combination were tabulated in Excel (Microsoft Corporation, Redmond, VA) where the weighted average of the standard deviations (the standard deviation within each zone being weighted by the number of yield data points in the zone) for the yield x zone map combination was calculated. This was used as the measure of within zone variability for the developed scoring system; this number is used as the denominator for calculating the Management zone scoring index (MZSI) and will be smaller for superior MZ classification methods. Superior MZ classification methods create more homogenous zones and therefore minimize intra-zone variability. From the same yield x zone map combination, the standard deviation of the average yield values from each zone was calculated. This measure was used to represent the inter-zone variability and was used as the numerator for calculating zone score. Converse to the measure of intra-zone variability, a superior MZ classification method would result in larger values of inter-zone yield variability. The measure of inter-zone variability was divided by the measure of intra-zone variability to result in the calculated zone score, so that the score reflects large values for MZ methods which maximize inter-zone variability (numerator) while minimizing intra-zone variability (denominator).

The MZSI is calculated as follows:

$$\text{MZSI} = \frac{\sigma_o \cdot \sum_{i=1}^{i=N} n_i}{\sum_{i=1}^{i=N} (\sigma_i \cdot n_i)} \tag{2}$$

where

MZSI = management zone scoring index

σ_0 = standard deviation of zone mean yields

N = number of zones

n_i = number of yield data points in the ith zone

σ_i = standard deviation of yield in the ith zone

The MZSI results were then tabulated and imported to JMP to perform a Student's t-test (α=.05) and one-way analysis of variance (ANOVA) to determine statistical significance across a range of comparisons. Prior to the statistical tests, the MZSIs were normalized using a univariate Box-Cox transformation (Box & Cox, 1964; Bailey, 2014) and outliers were removed, grouped by MZ delineation, using Tukey's method (Tukey, 1977). Tukey's method identifies outliers as data points residing beyond 1.5 * interquartile range outside the first and third quartiles. This methodology was applied to 19 yield data sets from nine fields across 204 MZs, which included: same-crop composite yield, different-crop composite yield, one year same-crop yield, one year different-crop yield, SSURGO, average EC, shallow EC, deep EC, true deep EC, ShEC/DpEC, SID BRT, SID Blue, and Elevation. Figure 1 displays a flow chart of this methodology.

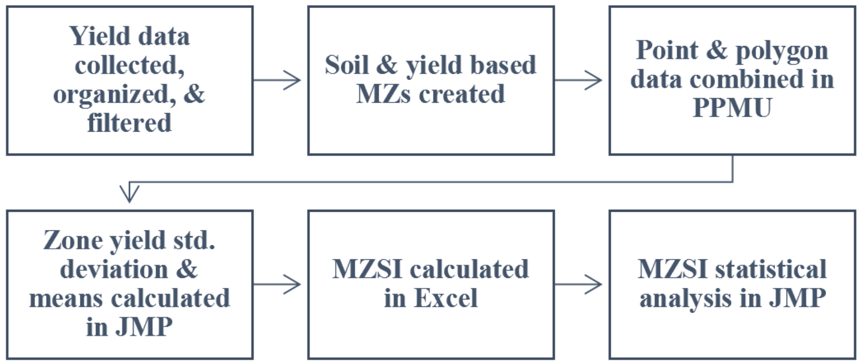

Figure 1. Methodology for calculating and comparing the management zone scoring index.

RESULTS AND DISCUSSION

Overall Zone Scoring

Comparisons were made for the overall data, which included yield data from both crops, dryland fields, and irrigated fields. Analyzing the data in this way suggests which MZ delineation methods work best when considered in both cotton and corn and suggests MZ delineation methods that should be used if one set of MZs is intended to be used across a given crop rotation. As seen in Table 1, there were significant differences in MZ Scores between MZ methods as indicated by a one-way ANOVA test ($F_{169,12}$=4.045, p<0.0001). The statistical grouping resulting in the highest MZSI Score included: same-crop composite yield maps, different-crop composite yield maps, and one year same-crop yield data. The statistical grouping resulting in the lowest MZSI Score included: Elevation, Sid (Blue), and true deep EC.

Table 1. Overall management zone scoring index

Method	n	SE[a]	Score[b]
Same-CompYield	5	0.100	0.964 (a)
Diff-CropCompYield	7	0.085	0.723 (abc)
1-yr Yield Map Same-crop	17	0.054	0.679 (ab)
Shallow EC/Deep EC	7	0.085	0.620 (bcd)
Shallow EC	19	0.051	0.595 (bcd)
Average EC	19	0.051	0.577 (bcd)
SSURGO	19	0.051	0.526 (d)
Deep EC	19	0.051	0.521 (d)
SID (Brightness)	15	0.058	0.499 (d)
1-yr Yield Map Diff-crop	14	0.060	0.499 (cd)
SID (Blue)	15	0.058	0.446 (de)
True Deep EC	7	0.085	0.444 (de)
Elevation	19	0.051	0.343 (e)

[a] SE = standard error

[b]Means with different letters indicate significant differences (Student's t-test, $p<0.05$)

Crop Specific Zone Scoring

When the MZSI is broken out by crop, some interesting trends emerged. In-crop composite yield maps and different-crop composite yield maps provided the two highest scores for both crops. Looking at only one-year yield data there was a significant difference in MZSI for cotton between different-crop and same-crop data. This suggests that one year of corn yield data did not accurately predict cotton yield potential based on the data in this study. Shallow EC/Deep EC performed well in both crops being in the top one or two statistical groupings. Shallow EC was the best performing soil-based zone delineation method for cotton while Shallow EC/Deep EC was the best soil-based method for corn. This measurement describes how much the topsoil varies from the subsoil. It is common in coastal plain soils to have a clay layer below the sandy topsoil, which holds more water than sandy soils. However, in both of these instances there were other soil-based methods that were not found to be significantly different in MZSI. Elevation was in the lowest statistical grouping for both crops. As seen in Table 2, there were significant differences in MZSIs between MZ methods for both crops as indicated by a one-way ANOVA (corn, $F_{88,12}$=2.897, p=0.0035) (cotton, $F_{68,12}$=3.759, p=0.0002).

Table 2. Crop-specific management zone scoring index

Corn				Cotton			
Method	n	SE[a]	Score[b]	Method	n	SE[a]	Score[b]
Same-Crop Comp Yield	3	0.121	0.888 (a)	Same-Crop Comp Yield	2	0.153	1.078 (a)
Diff-Crop Comp Yield	3	0.121	0.661 (abc)	Diff-Crop Comp Yield	4	0.108	0.769 (ab)
Shallow EC/Deep EC	5	0.094	0.609 (abc)	1-yr Yield Map Same-Crop	8	0.076	0.761 (ab)
1-yr Yield Map Same-Crop	9	0.070	0.608 (ab)	Shallow EC	9	0.072	0.760 (ab)
1-yr Yield Map Diff-Crop	8	0.074	0.561 (abc)	Average EC	9	0.072	0.706 (ab)
SID (Brightness)	9	0.070	0.558 (bc)	True Deep EC	2	0.153	0.668 (abcd)
SID (Blue)	9	0.070	0.485 (bc)	Shallow EC/Deep EC	2	0.153	0.648 (abcd)
Average EC	10	0.066	0.460 (bc)	Deep EC	9	0.072	0.625 (bc)
Shallow EC	10	0.066	0.446 (bcd)	SSURGO	9	0.072	0.618 (bc)
SSURGO	10	0.066	0.443 (cd)	1-yr Yield Map Diff-Crop	6	0.088	0.416 (cd)
Deep EC	10	0.066	0.427 (cd)	SID (Brightness)	6	0.088	0.412 (cd)
True Deep EC	5	0.094	0.354 (cd)	Elevation	9	0.072	0.409 (d)
Elevation	10	0.066	0.283 (d)	SID (Blue)	6	0.088	0.386 (d)

[a] SE = standard error

[b]Means with different letters indicate significant differences (Student's t-test, p<0.05)

Irrigated vs Dryland Zone Scoring

Under dryland conditions, soil-based MZs proved to be more comparable to yield-based MZs; the numerically highest MZ score was shallow EC followed closely by the 1 year same-crop yield map. Under dryland conditions soil water holding capacity is often the limiting factor for plant growth in many southeastern row crops. This could help explain why EC, which correlates to soil texture and moisture holding capacity, provided a higher MZSI. This also compliments Guo et al. (2012) who found that soil-based delineations have a higher correlation in dryer years. However, the only significant difference that was observed in the dryland data was that shallow EC was better than elevation at capturing the in-field variability of yield. Temporal variation, specifically rainfall, under dryland conditions is presumed to be the reason there was greater variability and little significant differences in this dataset.

Within the irrigated data, same-crop composite yield and different-crop composite yield were in the top statistical grouping. Yield-based MZs take into account every variable that affects crop growth throughout the season, while soil-based MZs only account for fixed variables such as soil texture, because of this yield maps can inherently do a better job at describing both temporal and spatial variability. As seen in Table 3, there were significant differences in MZ scores between MZ methods for irrigated data as indicated by a one-way ANOVA test ($F_{110,12}$=5.705, p<0.0001). The dryland MZSIs did not have significant differences by a one-way ANOVA ($F_{40,9}$=0.946, p=0.4949) but a Student's T test (p=0.05) demonstrated one pair of comparisons having a significant difference.

Table 3 Irrigated and dryland management zone scoring index

Irrigated				Dryland			
Method	n	SE[a]	Score[b]	Method	n	SE[a]	Score[b]
Same-Crop Comp Yield	5	0.079	0.964 (a)	Shallow EC	8	0.104	0.774 (a)
Diff-Crop Comp Yield	4	0.089	0.859 (ab)	1-yr Yield Map Same-Crop	4	0.147	0.741 (ab)
1-yr Yield Map Same-Crop	13	0.049	0.661 (bc)	Average EC	8	0.104	0.695 (ab)
Shallow EC/Deep EC	7	0.067	0.620 (bcd)	SID (Blue)	4	0.147	0.603 (ab)
SSURGO	11	0.053	0.523 (de)	Deep EC	8	0.104	0.598 (ab)
1-yr Yield Map Diff-Crop	10	0.056	0.513 (cde)	SID (Brightness)	4	0.147	0.596 (ab)
Average EC	11	0.053	0.491 (de)	Diff-Crop Comp Yield	3	0.170	0.542 (ab)
Shallow EC	11	0.053	0.465 (de)	SSURGO	8	0.104	0.530 (ab)
Deep EC	11	0.053	0.465 (de)	1-yr Yield Map Diff-Crop	4	0.147	0.464 (ab)
SID (Brightness)	11	0.053	0.464 (de)	Elevation	8	0.104	0.419 (b)
True Deep EC	7	0.067	0.444 (de)				
SID (Blue)	11	0.053	0.388 (ef)				
Elevation	11	0.053	0.288 (f)				

[a] SE = standard error

[b]Means with different letters indicate significant differences (Student's t-test, $p<0.05$)

Zone Division Method Scoring

As an additional demonstration of an application of MZSIs, a comparison of point data division strategies was completed comparing ½ standard deviation divisions to four equal divisions. This is an important factor in how the zones get divided and the size of the resulting zones. In classification by four equal divisions, the point data used to create the MZ's was divided equally into four separate zones, each zone containing ¼ of the data points. In classification by ½ standard deviation, divisions of the data used to create the MZs were defined in intervals of ½ standard deviation, with one of these zones being defined by a lower limit of the mean minus ¼ standard deviation and an upper limit of the mean plus ¼ standard deviation. While classification by ½ standard deviation provided a numerically higher score, the difference was not statistically significant.

It was concluded that the four-division method is probably adequate for precision agriculture applications. As seen in Table 4 there were significant differences between same-crop and different-crop yield-based MZs as indicated by a one-way ANOVA ($F_{49,3}$=10.543, p<0.0001). Overall, same-crop yield maps demonstrated a significantly higher MZSI than different-crop yield maps and therefore did a better job at capturing the yield variability than different-crop yield maps. This suggests that, if possible, MZs created from only one year of yield data should be used in the same crop for best division into relatively homogenous yield management areas. This analysis is presented as an example of another application of MZSI for assessment of zone development methods.

Table 4 Point data division strategies for yield data

Method	n	SE[a]	Score[b]
1-yr Yield Map Same-crop StDev	17	0.031	0.679 (a)
1-yr Yield Map Same-crop 4Div	12	0.037	0.636 (a)
1-yr Yield Map Diff-crop StDev	14	0.034	0.499 (b)
1-yr Yield Map Diff-crop 4Div	10	0.040	0.436 (b)

[a] SE = standard error
[b]Means with different letters indicate significant differences (Student’s t-test, p<0.05)

CONCLUSION

In every dataset in which it was included, same-crop composite yield maps achieved the highest MZSI. This demonstrates, at least from a quantitative view, that same-crop composite yield maps best maximize yield differences between zones and minimize yield differences within zones, when considering the tested MZs. This is logical because composite maps account for temporal variability by spanning multiple years. Also, same-crop yield maps consistently scored higher than different-crop yield maps, especially for 1-year maps. Based on these results it is not advisable to use 1-year of different-crop yield data to delineate MZ's. Same-crop yield MZs mostly scored higher than soil-based MZs. The exception to this was in the dryland data where there were no significant differences between yield- and soil-based MZs. Therefore, whenever it is available, even one year of same-crop yield data may be better to use for MZ delineation than soil-based methods.

In the absence of yield data, the best scoring soil-based MZ method was the ratio of Shallow to Deep EC. Possibly, the easiest and least expensive to obtain MZ delineation, USDA SSURGO, scored consistently in the middle of the results. With yield monitors being the most adopted PA technology, yield maps should be readily available and are better suited at describing spatial variability for development of relatively homogenous yield management zones. The worst performing MZ criteria elevation, resulting in the lowest MZSI in almost every scenario. Management zones developed for irrigated areas had more significant differences in scores compared to dryland fields, suggesting that consistently choosing the best MZ method for a given year on a dryland field may be challenging. Within most farm data management and GIS software applications, MZ divisions can be defined in multiple configurations. When four equal divisions were compared to ½ standard deviation divisions, the ½ standard deviation method provided a numerically higher score but there was no statistical difference. Therefore, four equal divisions more than likely provide enough resolution for most PA uses and at a lower cost.

In conclusion, for dryland and irrigated fields yield maps should be used to create management zones except in dryland fields where soil-based delineations also produced acceptable management zones. The MZSI is a viable methodology for comparing zone development methods. More work could be done to assess the comparisons presented here across a wider range of fields and production regions. The MZSI was presented here as a way of measuring zone suitability pertaining to yield; however, the same concepts could be assessed in future work pertaining to other aspects of spatial variability, such as pH. For instance, MZSI could be used to minimize intra-zone differences in recommended lime rates while maximizing inter-zone differences.

CHAPTER 3. EVALUATING ECONOMIC RETURNS OF GRID VERSUS MANAGEMENT ZONE SOIL SAMPLING AND HOW THEY RELATE TO SOIL FERTILITY

INTRODUCTION

Approximately 4,937,165 ha of cotton were planted in the United States in 2020 (USDA, 2020). According to Clemson University's *2021 Cotton Enterprise Budget*, the average cost of dryland cotton production is \$1,544 ha^{-1} in South Carolina. Fertilizer and lime costs make up approximately 20% of the total production cost, making these two of the highest inputs costs in cotton production (Clemson University, 2021).

Soil sampling is often the first step done in preparation for the growing season. It is the foundation for decisions on many subsequent management decisions and economic inputs. Accurately capturing the variability in soil fertility across a field will allow optimal fertilizer application to maximize yield. A properly collected soil sample will aid in determining which nutrients need to be applied to a field to meet the crop's nutrient requirements. Site-specific management aims to fine-tune existing production systems by collecting soil samples based on dividing the field into smaller management zones in order to implement variable rate applications of fertilizers, lime, and pesticides and take advantage of potential financial savings. A common method of dividing a field is grid sampling. Grid sampling is the process of dividing the whole field into equal sized, square areas where sampling can then take place. Generally, large grid areas (e.g., > 2 ha) provide reduced resolution of the actual variability within the field, however, sampling cost and analysis is concurrently reduced. Small grid areas (e.g., < 2 ha) provide increased resolution, but with a greater number of samples, costs are higher due to increased costs of sample analysis.

In order to implement variable rate applications of fertilizers to take advantage of potential savings, fields must be divided into MZs. Management zones are created from data relating to a field's spatial variability to determine areas with similar properties such as soil texture or yield potential. A wide range of yield and soil spatial data can be collected on-farm. These datasets can be utilized in several ways to create management zones. Depending upon the size and criteria used for zone definition, zones can vary in how effective they are at describing the variability in the field. After establishment of a MZ, one composite sample is collected from each zone. One of the most common technologies for documenting spatial variability is soil electrical conductivity (EC). Soil EC offers a relatively low cost and quick method to delineate field variability. Soil EC can be related directly to soil texture (Doolittle et al., 1994). However, soil EC can be affected by properties other than soil texture. Soil moisture, salinity, or recent applications of inputs like manure can significantly alter EC readings (Grisso, 2009).

Another field characteristic for zone delineation is the level of soil organic matter. On-the-go soil organic matter (OM) sensors have recently been developed (Lund 2011). Increased organic matter content has been shown to relate to higher yields (Bauer, 1994). Lund (2011) demonstrated that on-the-go OM sensors accurately matched lab analyzed samples in coastal plain soils of the southeast. Estimated OM had an R^2 of 0.82, 0.86 when compared to lab analyzed samples in Georgia and Alabama respectively (Veris Technologies, 2012). Another data layer used for zone delineation are the soil maps developed by the USDA's Web Soil Survey (SSURGO). This database of soil maps and other datasets is the largest in the world and covers approximately 95% of the United States (USDA, 2020). However, these soil maps are only intended for general farm use and planning; the resolution is not suitable for definition of in-field variability. On the web soil survey website, it even has a disclaimer that it's maps may not be valid at field scale because the maps were created at a scale of 1: 24,000. At this scale one centimeter on the map equals 240 m on the ground. Despite this inadequacy many farm data management platforms are using SSURGO as a base default layer.

When applying fertilizer at a uniform rate, it is inevitable that some areas where fertilizer was applied, will not match the fertility requirement. Uniform fertilizer rates will lead to over or under application in some areas, thus lowering nutrient use efficiency and increasing potential negative environmental impacts. Variable rate application technology for fertilization was introduced in the 70's but adoption rates has been slow. Variable rate technology often comes with a high initial capital investment by the grower and actual profits have been inconsistent (Schimmelpfennig, 2016). The goal of any variable rate fertilizer application is to match the application rate to the nutrient requirements of the crop throughout the field. Babcock et al. (1998) showed that, in Iowa, variable rate technology in corn produced an increase in return of up to \$18.35 ha^{-1} compared to conventional application methods. Variable rate control technologies are available, now the most profitable methods of developing variable rate prescriptions must be determined.

This research sets forth the methodology to calculate the cost of sub-optimal management (CSM) as a measurement of the economic returns associated with MZs and grids. The CSM for each zone delineation method is calculated from the sum of: cost of excess fertilizer applied, the estimated yield loss from under application of fertilizer, the estimated dollar value of yield loss resulting from sub-optimal pH, and the associated cost to obtain soil fertility samples and analyses. A CSM of \$0 ha^{-1} would theoretically mean that at every point in the field the fertilizer needs were met exactly with no over or under application, the resulting pH from lime application was exactly correct, and this was achieved with no sampling or analysis costs.

Grid soil sampling

Soil samples are a major factor of fertilizer recommendations. A fertility recommendation can be created when combined with plant nutrition requirements of a selected crop to reach a predetermined yield goal. However, collecting an accurate soil sample is not as simple as it sounds. Rains et al. (2001) demonstrated the many problems possibly associated with soil sampling. Where a 26 ha irrigated cotton field was sampled using three methods:1) 1 ha grids, 2) MZs delineated from yield data and 3) farmer knowledge. They also collected samples from 3 depths; 0-7.5 cm, 7.5-15 cm, and 0-15 cm. The samples were sent to two different labs in order to compare nutrient analysis and fertilizer recommendations. They found that every one of the above-mentioned factors had a significant impact on the resulting fertilizer and lime recommendations. Soil properties can vary greatly across a field. Poor placement of soil samples, causing the variability of the field not to be accurately captured, can impact the nutrient analysis and thus affect the fertilizer recommendation.

Fertilizer is one of the costliest inputs in crop production. Therefore, growers must pay attention to how and where samples are collected to ensure accurate recommendations.

The simplest method of capturing within-field variability is grid sampling. However, growers deciding what grid size to use to most accurately estimate the variability in a field is often unknown. Past research suggests smaller grid sizes are better than larger grids at quantifying the variability of nutrients in a field. Nanni et al. (2011) evaluated five different grid sizes starting with 1 ha grids and increasing grid size to 7.2 ha. They concluded that their smallest grid size, 1 ha, were too large to capture the variability of soil nutrients such as phosphorus and potassium. Martins et al. (2018) tested various soil sampling grid sizes down to 0.04 ha. Similarly, the smallest grid size was found to be the most accurate in terms of depicting soil variability. This makes sense because more samples will inevitably lead to a more accurate representation of the actual in-field variability, However, both studies failed to define is at what point did the positive economic return of sampling smaller grids end. Wollenhaupt et al. (1994) and Franzen et al. (1995), probably had the two studies most relevant to this project. They estimated that the optimum sampling density, for a commercial setting, was around 0.4 ha.

Soil sampling is costly; each sample generates labor, handling, and laboratory analysis costs. In their review of soil sampling strategies Lawrence et al. (2019), were unable to find any literature defining an Economically Optimum Sampling Density (EOSD) in agricultural settings. However, they believed that the EOSD is an important metric that merits attention in future research. One of the main objectives of this study is to determine the economically optimum grid sampling size.

Management Zone Soil Sampling

As compared to grid sampling, Management Zone (MZ) sampling generally requires less samples while striving to create data that is just as accurate. However, just as with grid sampling, MZ sampling can be complicated. A MZ can be created from any dataset that you can reference spatially across a field. With recent advancements in data collection such as unmanned aerial vehicles, near real-time satellite imagery, and many new sensor technologies, there are now many datasets that can measure field variability. To add complexity, MZs can be created from any combination of datasets.

Previous studies evaluating soil sampling methods as criteria for creating MZs have produced mixed results. Schepers et al. (2004) evaluated if soil characteristics could be used to produce MZs that accurately describe soil spatial variability. They created MZs in an irrigated corn field using bare soil imagery, elevation, and EC. They found that even under irrigation, throughout the five-year study, temporal variability played a huge role in the resulting yields, so much so, that they concluded that use of the MZs would only be appropriate in three of the five years. Sawchik et al. (2007) compared two grid sizes (0.18 ha & 1.0 ha) to zones derived from soil survey maps (SSURGO), elevation, and soil EC. They concluded that while MZs often identified areas with differing yield, they were less effective than either of the grid sampling methods at describing the within-field variation of soil tests and yield response to fertilization. Mzuku et al. (2005) demonstrated that MZs created from bare soil imagery plus farmer's knowledge of topography and past management resulted in MZs that showed significant spatial correlation with several measureable soil parameters including bulk density, organic matter, texture, and compaction. However, as with grid sampling, studies on the economic impact of the accuracy of derived fertilizer applications and costs associated with soil sampling based on

MZ's is very limited (Nawar, 2017). One of the objectives of this study is to estimate economic returns of various MZs.

Spatial Variability of Nutrients

The three main fertilizers applied to agricultural fields, nitrogen, phosphorus (P) and potassium (K), all behave differently in the soil. Nitrogen is very mobile and therefore leaches in sandy soils, whereas phosphorous is considered immobile and does not move as much in the soil profile. Potassium is mobile in sandy soils, though not to the degree of nitrogen. Pinpointing fertility levels of a nutrient across a field, and the most accurate sampling method, has proven to be difficult. Lauzon et al. (2005) studied the variation in phosphorus, potassium, and pH across 23 fields by sampling in a 0.09-hectare grid pattern. They concluded that even the 0.09-hecatre grid was not small enough to effectively capture the variation and concluded that grid sampling would not be a practical method of capturing soil nutrient variability. Conversely, Lawrence et al. (2019) recommended a structured sampling method, grids, over MZs for phosphorus and pH because of their random dispersion and dependence on previous fertilizer applications or field history. They also found that for more mobile nutrients like nitrogen and potassium, MZs could be appropriate because several studies have shown correlation between soil properties and nutrient level. If the soil is acidic (pH<5.5) liming will increase phosphorus availability in the soil but increasing pH beyond 6.2 can cause some micronutrients to become less available to the plant (Cristie, 2021).

Mallarino et al. (2005) also found that a grid sampling strategy of 1.0 ha or less is better for testing soil phosphorus levels and that zone sampling may only be practical when soil test phosphorus levels are high. This suggests that the spatial variation of phosphorus is the limiting factor in applying precision agriculture technology to soil sampling. Due to its seemingly random dispersion and the great effect that previous fertilizer applications or land use have on soil test phosphorus levels, grid sampling appears to be the currently recommended method for capturing phosphorus variability. If a field has to be grid sampled for meaningful soil phosphorus data, then a farmer is not likely to sample the field a second time using a MZ strategy no matter how accurate it may be for the more mobile nutrients such as potassium. However, no research is available on the economic feasibility of zone versus grid sampling for soil P. One of the objectives of this study is to determine the most economically viable method for capturing the spatial variability of phosphorus and potassium.

OBJECTIVES

The objectives of this study were to evaluate the economic returns of various grid and zone soil sampling methods as they relate to soil fertility by: (1) determining and comparing the cost of sub-optimal management (CSM) for several soil sampling strategies, (2) determining the economically optimum grid sampling size (EOGSS), and (3) evaluating how accurate each method captures the spatial variability of soil nutrients.

METHODS & MATERIALS

Seven fields, totaling 204 ha, in the coastal plain region of South Carolina were soil sampled using grid sizes of 0.4, 0.49, and 0.61 ha. These fields were selected for sampling because they are representative of the field conditions and management practices common in the region. Samples were sent to the Clemson University Ag Services Lab for standard soil fertility analysis. Additionally, these soil samples were analyzed for sand, silt, clay, and organic matter content. Soil texture was measured using the hydrometer method (Huluka 2014) and organic matter was measured using the loss on ignition method (Zhang 2014). To simulate larger sampling grids (e.g. 1.6, 3.6, 6.5, etc. ha grids) sample results were numerically combined for adjacent grids. For example, if the field was sampled on 0.4 ha grids, four adjacent grids (2 x 2) were combined to represent one 1.6 ha grid and the four sample results were averaged (Figure 2). A similar method was performed to combine nine adjacent grids (3 x 3) and sixteen adjacent grids (4 x 4).

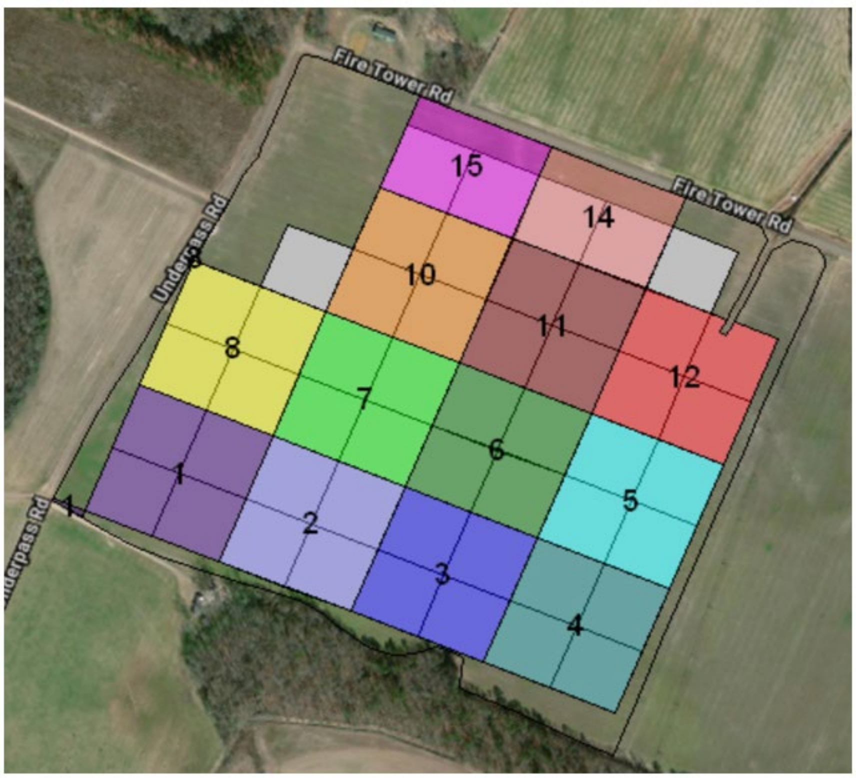

Figure 2. An example of how smaller grids were numerically combined to represent larger grids

Then, for the purpose of comparison, the simulated grids were grouped into three categories; small grids (<2.4 ha), medium grids (2.4 to 5.5 ha), and large grids (>5.5 ha). A uniform management strategy (whole field) was also created by averaging the soil sample results from every sample in the field. Soil EC and elevation data were obtained through use of a Veris 3100 EC cart (Veris Technologies, Salina, KS). A true deep EC value was calculated from the Veris data in order to get a reading representing only the deeper soil (30-90 cm) because shallow EC readings represent 0-30 cm depth and deep EC readings represent 0-90 cm depth. Therefore, deep EC includes both shallow and true deep EC. Theoretically this calculated true deep EC value represents the soil depth of 30-90 cm. United States Department of Agriculture SSURGO soil type maps were also evaluated as they are often used to delineate MZs. Abbreviations were assigned for some of the datasets and are as follows: organic matter (OM), soil clay content (CLAY), and soil sand content (SAND). From these datasets, contour maps were created in Farmworks software (Trimble Inc., Sunnyvale, CA). Contours were created with the following settings: 15.24 m averaging, 0% smoothing, and no minimum area. After contour maps were generated for each dataset, the data was processed through Point Polygon Merge Utility (PPMU) software (Kirk, 2016). As shown in Figure 3, PPMU allows point data to be overlaid on each grid and contour map to identify the zone or grid (polygon) in which each point resides. The combined data was then analyzed using JMP statistical software (SAS Institute, Cary, NC) to create an XY scatter plot for MZs plotted against soil nutrient analysis.

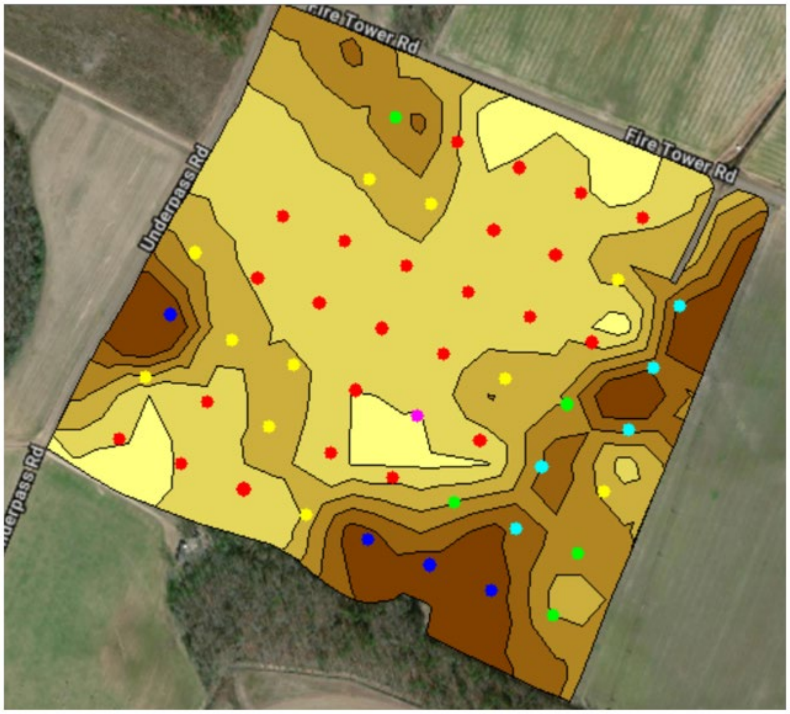

Figure 3. Displays a point dataset(.csv) overlaid on a polygon (.shp) dataset

Based on the current Clemson University soil test recommendations (Clemson University, 2021) with a yield goal of 1009 kg ha^{-1} of lint cotton, phosphorus was deemed deficient if soil levels were below 202 kg ha^{-1} and potassium was deemed deficient if soil levels were below 247 kg ha^{-1}. These values were calculated from the Clemson University soil test recommendations for irrigated cotton (Clemson University, 2021). The target soil phosphorous and potassium levels were plotted as a function of soil test levels derived from a sample and the recommended application amount. For example, according to Clemson University soil test recommendations, if a soil is deemed to have low potassium (<95 kg ha^{-1} K_2O) then an application of 155 kg ha^{-1} K_2O is recommended for a potential sum of 250 kg ha^{-1} K_2O. Lime recommendations were calculated using Adams et al. (1962) buffer formula with a target pH of 6.2. The average soil fertility levels within each simulated grid or zone were used to calculate the fertilizer and lime recommendation to be applied in order to reach the recommended level. Diammonium phosphate, 18-46-0, (DAP) and muriate of potash, 0-0-60, (MOP) were assumed as sources for phosphorus and potassium for the purposes of cost analysis. The prescribed fertilizer and lime rate for each grid or zone was then compared to the recommendation for each soil sample point to calculate over or under application at each point. A dollar value was then associated with the excess cost of MOP by considering any fertilizer applied above the required amount as wasted at \$429 MT^{-2} MOP. Excess cost for DAP was calculated but not included in this analysis because DAP does not leach or move in the soil so it was assumed that any excess, barring runoff/erosion, would be available to the following crop (Crozier, 2010). To explain, if growers soil sample annually, samples in the year following an excessive application of DAP should reflect the excess and the rate applied that year would then be reduced proportionately. There is evidence in the literature that yield response to nutrient level can be quite variable (Crozier, 2010; Perez, 2005; Wittry, 2004), with no general consensus on trend in yield response as a function of nutrient level. Even state operated soil test laboratories recommend nutrient application when a yield response is only observed 50% of the time (Clemson University, 2021; Kissel, 2011; Hardy, 2014; Hatfield, 1972). While it would be ideal to have a better understanding of yield response to nutrient level for inclusion in this analysis, because this relationship is not consistent, it was assumed for this work for both DAP and MOP that if fertilizer was under-applied by a certain percentage of the target nutrient level then yield would be reduced by the same percentage from the 1009 kg ha^{-1} lint cotton yield goal set by the soil fertility requirements. However, only the one nutrient deemed most deficient was used to reduce the simulated yield.

The assumed cost of lint cotton was $1.54 kg^{-3} which was used to determine the cost associated with yield loss due to over or under-application of fertilizer. At each point, a resulting soil pH from the prescribed lime application was calculated by rearranging the Adams-Evans buffer formula so that instead of calculating the lime recommendation from the soil test pH, the theoretical pH resulting from the application of a specified amount of lime was calculated. Yield losses resulting from not achieving the optimal pH were assigned using data from Adams (1968) by plotting the data and calculating the trend line formula.

The resulting yield potential based on the pH resulting from a lime application is calculated as follows:

$$\%\ yield\ potential = \frac{-598.3 * x^2 + 7440.3 * x - 21281}{1850.399} \tag{3}$$

where

x = resulting pH

Wollenhaupt et al. (1994) calculated a sampling cost based on grid sampling by grid size with seven cores per sample for each grid/zone. A trend line formula was derived from this data and used for sampling cost calculations in this study. They considered a labor cost of $25 per hour and $6.00 per sample analysis cost. These costs were adjusted for inflation (U.S. Bureau of Labor Statistics, 2021) before calculation. Sampling costs were calculated as follows:

$$\text{Sampling Cost } (\$\ \text{ha}^{-1}) = 15.279\text{x}^{-1.013636} \quad (4)$$

where

x = sampling grid or zone size (ha)

Sampling costs, sub-optimal pH yield loss costs, potassium or phosphorus deficiency yield loss costs, and MOP excess fertilizer costs were totaled for each method, which resulted in the CSM. As sample grids get smaller, the sampling cost per unit area increases but the other components for calculation of CSM should decrease. An economically optimum grid sampling size (EOGSS) was calculated by plotting sampling costs and their associated CSMs (less sampling cost), both as a function of grid sizes. The grid sample size at which the sum of sampling cost and CSM was the lowest was deemed the EOGSS, since it represents minimization of total cost.

Spatial variability of soil phosphorus and potassium levels were related to all of the zone delineation methods. In order to analyze this across several sites and years, both the soil phosphorus & potassium levels and the comparative zone delineation methods were normalized. Then, for point data (e.g. EC), all of the data points were averaged within the small grid definition (<2.4 ha) for each site. For example, if the site was sampled on a 0.4 ha grid then every EC data point inside each 0.4 ha grid polygon was averaged to create a singular EC value for each grid polygon. An XY scatter plot was created in a similar manner as before to evaluate each zone delineation method's ability to relate to the spatial variability of soil nutrients.

The CSMs were imported into JMP to perform a Student's t-test (p=.05) and an analysis of variance (ANOVA) to determine significance difference as discussed in results. Prior to the statistical tests, the CSMs were normalized using a univariate Box-Cox transformation (Box & Cox, 1964; Bailey, 2014) and outliers were removed, grouped by MZ delineation, using Tukey's method (Tukey, 1977). Tukey's method identifies outliers as data points residing beyond 1.5 * interquartile range outside the first and third quartiles.

RESULTS & DISCUSSION

Site 1 (Back)

Site one is a 27 ha field, which is moderately variable in soil properties for the region. The soil texture ranges from 2.9% to 10% clay content. It is gently sloping with a couple of clay knolls. Year 2018 was the first time that this field had been in agricultural production for many years. Soil fertility, texture, and organic matter samples were collected on a 0.4 ha grid. Small, medium, and large composite grids were created from 2x2, 3x3, and 4x4 adjacent 0.4 ha grid squares for analysis. Among all methods, shallow EC achieved the lowest CSM at \$359.15 ha^{-1} and medium grids performed the worst with a CSM of \$488.24 ha^{-1}(Table 5). When sample costs and CSM, minus sampling cost, were plotted as a function of grid size, the EOGSS for Site 1 was calculated to be 1.29 ha.

Table 5. Costs of sub-optimal management as a function of grid and zone delineation method for Site 1 (sorted by total CSM from lowest to highest)

Method	Sample Cost	Sub-optimal pH Cost	K2O or P2O5 Deficiency Cost	K2O Excess Cost	Total CSM
	($/ha^{-1})	($/ha^{-1})	($/ha^{-1})	($/ha^{-1})	($/ha^{-1})
SSURGO	2.37	79.33	258.79	18.66	359.15
Shallow EC	2.83	71.11	267.88	18.29	360.11
Average EC	3.23	78.19	262.09	18.01	361.52
Deep EC	3.38	83.76	270.95	18.11	376.20
Sand	3.08	69.10	286.37	18.17	376.72
OM	3.12	71.17	284.90	18.02	377.21
Clay	2.75	79.70	280.70	18.05	381.20
Small Grid	8.99	80.02	276.60	16.91	382.52
Alt	3.33	102.55	283.81	19.52	409.21
Large Grid	2.29	93.83	300.92	19.56	416.60
Whole Field	0.49	112.92	309.38	12.43	435.22
Medium Grid	3.94	111.27	355.37	17.66	488.24

Site 2 (Shack)

Site two was similar to Site 1; it is a 27.5 ha field and has a soil clay content ranging from 2.8% to 8.8%. It is generally flat and slightly sloped towards the southeast corner. Similar to Site 1, Site 2 was returned to an agricultural rotation in 2018 after many years of native growth. Soil fertility, texture, and organic matter samples were collected on a 0.4 ha grid. Larger grid sizes were created for analysis, from 2x2, 3x3, and 4x4 adjacent grid polygons. Medium grids provided the lowest CSM at $192.05ha^{-1}. Whole field returned the highest CSM at $402.20 ha^{-1}(Table 6). When sample costs were plotted against the CSM's for each grid size, the EOGSS for this site was calculated to be 0.69 ha.

Table 6. Costs of sub-optimal management as a function of grid and zone delineation method for Site 2 (sorted by CSM from lowest to highest)

Method	Sample Cost ($/ha^{-1})	Sub-optimal pH Cost ($/ha^{-1})	K2O or P2O5 Deficiency Cost ($/ha^{-1})	K2O Excess Cost ($/ha^{-1})	Total CSM ($/ha^{-1})
Medium Grid	3.94	32.65	136.75	18.71	192.05
Large Grid	2.29	63.15	191.60	18.46	275.50
Sand	3.08	41.64	228.43	18.85	292.00
OM	3.12	45.06	232.43	18.55	299.16
Elevation	3.33	71.30	212.96	19.69	307.28
Average EC	3.23	47.96	245.58	17.86	314.63
Deep EC	3.38	48.12	246.60	17.97	316.07
Shallow EC	2.83	59.50	235.51	18.30	316.14
Clay	2.75	80.44	222.52	19.11	324.82
SSURGO	2.37	73.54	235.76	18.53	330.20
Small Grid	8.99	49.94	320.56	18.01	397.50
Whole Field	0.49	87.41	303.26	11.04	402.20

Site 3 (White Barn)

Site three was a 21.4 ha highly variable field. This field slopes towards the center in all directions. It contains heavy bottom land in the center which transitions to lighter sandier soils along the edge. In the bare soil aerial image, Figure 4, one can clearly see the differences

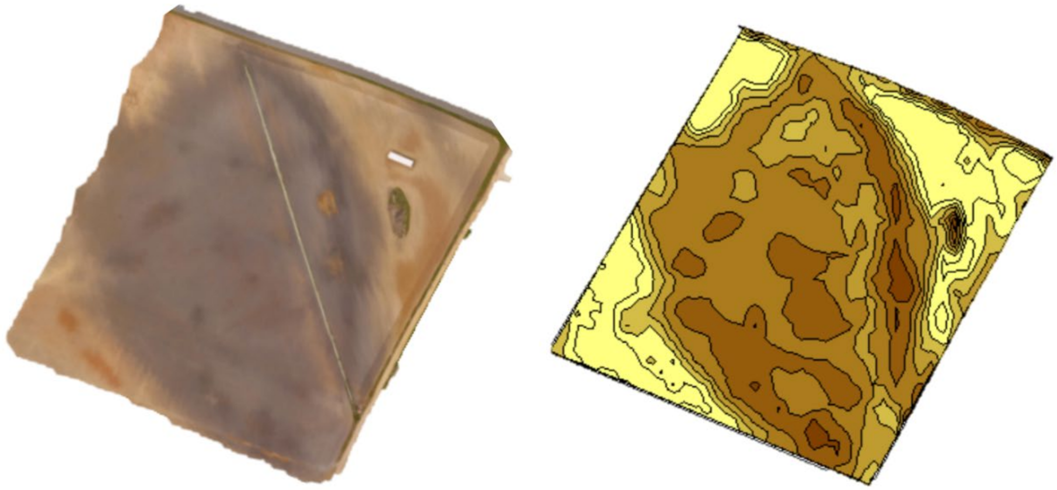

Figure 4. Aerial Imagery of Site 3(left), Soil clay content (right)

in soil color. There is a drainage ditch in the center, which was excluded from the field boundaries. Clay content ranges from 5.3% to 30.5%. This field was returned to an agricultural rotation in 2018 after approximately 5 years of fallow. Soil fertility, texture, and organic matter samples were collected on a 0.4 ha grid. Larger grid sizes were created for analysis, from 2x2, 3x3, and 4x4 adjacent grid polygons. Management zones derived from sand content produced the lowest CSM at \$284.82 ha^{-1}. Sand content had the lowest sub-optimal pH cost suggesting that sand content may be a valuable dataset pertaining to pH. The largest grids resulted in the highest CSM at \$484.54 ha^{-1}. When sample costs were plotted against the CSM's for each grid size, the EOGSS for Site 3 was calculated to be 0.34 ha.

Table 7. Costs of sub-optimal management as a function of grid and zone delineation method for Site 3 (sorted by CSM from lowest to highest)

Method	Sample Cost ($/ha^{-1})	Sub-optimal pH Cost ($/ha^{-1})	K2O or P2O5 Deficiency Cost ($/ha^{-1})	K2O Excess Cost ($/ha^{-1})	Total CSM ($/ha^{-1})
Sand	3.08	27.54	241.92	12.28	284.82
OM	3.12	58.16	241.74	12.12	315.14
Clay	2.75	53.05	254.17	13.09	323.06
SSURGO	2.37	86.10	261.17	12.67	362.31
Small Grid	8.99	57.48	285.07	13.03	364.57
Shallow EC	2.83	79.88	269.46	14.51	366.68
Elevation	3.33	77.23	277.49	14.21	372.26
Medium Grid	3.94	63.99	301.98	16.81	386.72
Deep EC	3.38	80.38	293.39	13.29	390.44
Average EC	3.23	102.42	305.12	14.85	425.62
Whole Field	0.49	170.07	299.10	11.97	481.63
Large Grid	2.29	121.44	346.50	14.31	484.54

Site 4 (Market Back)

Site four was a 27.9 ha field, with average variability for the region. In this study, Site four had samples collected from 2 consecutive years 2017 & 2018. This field was in agricultural rotation for all of recent history. In 2017, soil fertility, texture, and organic matter samples were collected on a 0.4 ha grid. Larger grid sizes were created for analysis. The clay contents ranged from 2.5% to 4.5%. Small grids provided the lowest CSM at \$229.65 ha^{-1}. The SSURGO soil map provided the highest CSM at \$340.74 ha^{-1}. Phosphorus deficiency was the costliest CSM component in all methods. When sample costs were plotted against the CSM's for each grid size, the EOGSS for this site was calculated to be 0.64 ha.

Table 8. Costs of sub-optimal management as a function of grid and zone delineation method for Site 4 in 2017 (sorted by CSM from lowest to highest)

Method	Sample Cost ($\$/ha^{-1}$)	Sub-optimal pH Cost ($\$/ha^{-1}$)	K2O or P2O5 Deficiency Cost ($\$/ha^{-1}$)	K2O Excess Cost ($\$/ha^{-1}$)	Total CSM ($\$/ha^{-1}$)
Small Grid	8.99	27.00	177.18	16.48	229.65
Elevation	3.33	29.19	209.99	17.59	260.10
Sand	3.08	27.08	218.33	16.52	265.01
Medium Grid	3.94	27.55	222.92	16.06	270.47
Large Grid	2.29	21.84	254.64	16.70	295.47
Clay	2.75	27.28	248.74	16.80	295.57
Whole Field	0.49	37.12	250.01	8.49	296.11
OM	3.12	33.73	268.64	18.15	323.64
Shallow EC	2.83	33.32	279.17	16.55	331.87
Deep EC	3.38	35.65	281.84	16.75	337.62
Average EC	3.23	34.15	285.16	16.62	339.16
SSURGO	2.37	30.47	291.03	16.87	340.74

In 2018, soil fertility and organic matter samples were collected from Site 4 on the same 0.4 ha grid. Soil texture and organic matter were believed to remain the same therefore the same data was used for both years. Larger grid sizes were created for analysis. Sand content provided the lowest CSM at $\$311.51$ ha^{-1}. The SSURGO soil map provided the highest CSM at $\$418.91$ ha^{-1}. Phosphorus was the costliest nutrient deficiency in all MZs. When sample costs were plotted against the CSM's for each grid size, the EOGSS for this site was calculated to be 0.55 ha.

Table 9. Costs of sub-optimal management as a function of grid and zone delineation method for Site 4 in 2018 (sorted by CSM from lowest to highest)

Method	Sample Cost ($/ha^{-1})	Sub-optimal pH Cost ($/ha^{-1})	K2O or P2O5 Deficiency Cost ($/ha^{-1})	K2O Excess Cost ($/ha^{-1})	Total CSM ($/ha^{-1})
Sand	3.08	36.48	253.33	18.62	311.51
Small Grid	8.99	35.31	252.13	18.30	314.73
Large Grid	2.29	40.62	283.12	18.46	344.49
Clay	2.75	32.88	298.02	17.82	351.47
Shallow EC	2.83	36.93	305.03	17.81	362.60
Average EC	3.23	38.02	304.92	17.70	363.87
Medium Grid	3.94	36.50	306.08	18.09	364.61
Deep EC	3.38	38.68	307.83	17.85	367.74
Elevation	3.33	33.27	319.86	18.19	374.65
OM	3.12	39.96	320.35	19.71	383.14
Whole Field	0.49	40.60	344.37	11.54	397.00
SSURGO	2.37	35.33	362.72	18.49	418.91

Site 5 (Market Front)

Site five was a 32 ha field which has been in an agricultural rotation for many years. Soil clay contents ranged from 5% to 6.75%. Soil fertility, texture, and organic matter samples were collected on a 0.49 ha grid. Larger grid sizes were created for analysis. Shallow EC resulted in the lowest CSM at $174.38 ha^{-1} and whole field resulted in the highest CSM at $303.40 ha^{-1}. Potassium was the costliest nutrient deficiency in all delineation methods with almost every method recommending zero DAP application. Soil sample phosphorus (P_2O_5) levels were as high as 437 kg ha^{-1}. When sample costs were plotted against the CSM's for each grid size, the EOGSS for this site was calculated to be 0.42 ha.

Table 10. Costs of sub-optimal management as a function of grid and zone delineation method for Site 5 (sorted by CSM from lowest to highest)

Method	Sample Cost ($/ha^{-1})	Sub-optimal pH Cost ($/ha^{-1})	K2O or P2O5 Deficiency Cost ($/ha^{-1})	K2O Excess Cost ($/ha^{-1})	Total CSM ($/ha^{-1})
Shallow EC	2.83	44.18	111.00	16.37	174.38
Deep EC	3.38	46.57	117.59	16.20	183.74
True Deep EC	2.93	45.31	119.49	16.27	184.00
Average EC	3.23	46.77	119.57	16.18	185.75
Large Grid	2.29	56.32	124.61	19.06	202.28
Small Grid	8.99	49.63	131.56	18.18	208.36
Sand	3.08	49.97	147.20	17.84	218.09
True Deep EC/Shallow EC	2.10	53.49	145.80	19.61	218.90
OM	3.12	53.88	144.51	18.44	219.95
Elevation	3.33	51.00	149.68	18.16	222.17
SSURGO	2.37	53.60	167.70	20.55	244.22
Medium Grid	3.94	48.03	184.65	18.66	255.28
Clay	2.75	54.01	191.22	22.50	270.48
Whole Field	0.49	54.80	232.66	15.45	303.40

Site 6 (Big Pivot West)

Site six was a 39 ha field that was relatively flat for the region. The difference in elevation is no more than 1.2 m from the lowest spot to the highest. Clay contents ranged from 3.5% to 9.3%. Soil fertility, texture, and organic matter samples were collected on a 0.61 ha grid. Larger grid sizes were created for analysis. Management zones derived from shallow EC resulted in the lowest CSM at $299.33 ha^{-1} and deep EC resulted in the highest CSM at $460.00 ha^{-1}. Upon further investigation the shallow EC map has larger zone sizes than deep EC and more clear-cut divisions between MZs (Figure 5). When sample costs were plotted against the CSM's for each grid sampling size, the EOGSS for this site was calculated to be 0.33 ha.

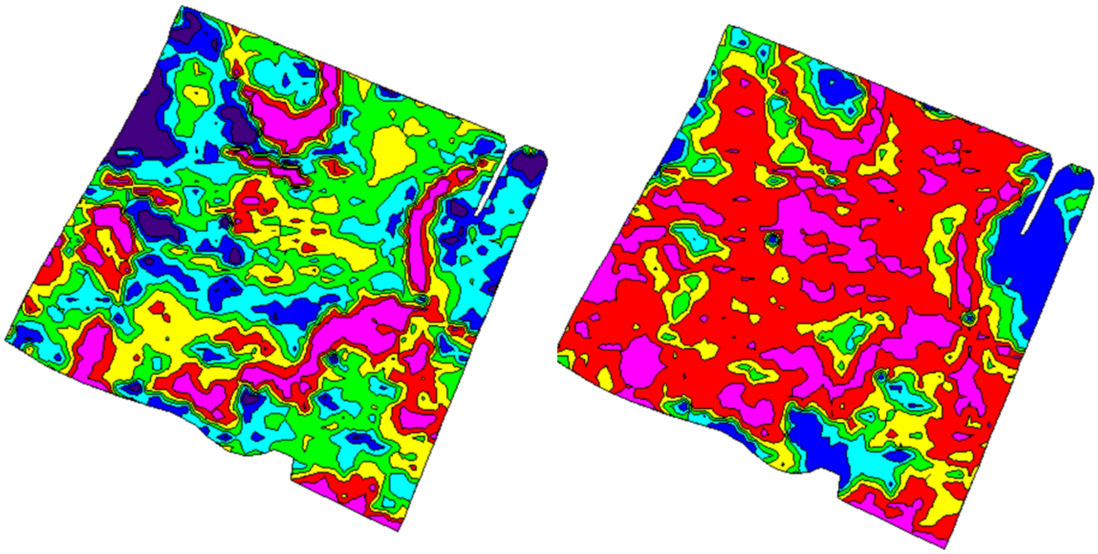

Figure 5. Deep EC contour map (left) has smaller MZs than shallow EC (right)

Table 11. Costs of sub-optimal management as a function of grid and zone delineation method for Site 6 (sorted by CSM from lowest to highest)

Method	Sample Cost ($/ha^{-1})	Sub-optimal pH Cost ($/ha^{-1})	K2O or P2O5 Deficiency Cost ($/ha^{-1})	K2O Excess Cost ($/ha^{-1})	Total CSM ($/ha^{-1})
Shallow EC	2.83	67.26	212.84	16.40	299.33
Sand	3.08	63.94	225.17	17.07	309.26
True Deep EC/Shallow EC	2.10	81.33	228.41	16.32	326.06
OM	3.12	74.42	232.18	16.72	326.44
Small Grid	8.99	100.20	206.28	15.67	331.14
Medium Grid	3.94	153.72	202.51	16.24	376.41
Large Grid	2.29	140.80	229.14	17.01	389.24
SSURGO	2.37	122.62	256.10	17.30	398.39
Clay	2.75	143.99	249.58	17.39	413.71
Average EC	3.23	181.13	226.28	17.00	427.64
Elevation	3.33	176.72	235.86	19.18	435.09
True Deep EC	2.93	167.03	251.82	14.46	436.24
Whole Field	0.49	172.70	261.59	11.00	445.78
Deep EC	3.38	224.05	215.97	16.60	460.00

Site 7 (Tommy's)

Site seven was a 29.54 ha field that is also relatively flat. Total elevation difference from the highest point to the lowest point is approximately 1.2 m. Soil fertility samples were collected for two consecutive years (2017 and 2018) in this field. Soil fertility, texture, and organic matter samples were collected on a 0.4 ha grid. Soil texture and organic matter were believed to remain the same therefore the same texture data was used for both years. Clay contents ranged from 2.6% to 6.4%. Larger grid sizes were created for analysis. Medium Grids (3.2 ha) resulted in the lowest CSM for Site 7 in 2018 at \$249.21 ha^{-1} and true deep EC resulted in the highest CSM at \$403.66 ha^{-1}. Once again phosphorus represented the costliest nutrient deficiency in all management zone and grid methods with medium grids having the least costly phosphorus deficiency. Average EC resulted in the lowest potassium deficiency cost. When sample costs were plotted against the CSM's for each grid size, the EOGSS for this site in 2018 was calculated to be 0.6 ha.

Table 12. Costs of sub-optimal management as a function of grid and zone delineation method for Site 7 in 2018 (sorted by CSM from lowest to highest)

Method	Sample Cost ($/ha^{-1})	Sub-optimal pH Cost ($/ha^{-1})	K2O or P2O5 Deficiency Cost ($/ha^{-1})	K2O Excess Cost ($/ha^{-1})	Total CSM ($/ha^{-1})
Medium Grid	3.94	54.38	170.55	20.34	249.21
Small Grid	8.99	34.94	195.74	18.66	258.33
Average EC	3.23	55.08	194.76	18.24	271.31
Shallow EC	2.83	47.15	208.22	18.10	276.30
Sand	3.08	33.71	228.16	18.15	283.10
Clay	2.75	49.40	224.99	18.59	295.73
OM	3.12	23.60	250.72	18.68	296.11
Elevation	3.33	83.20	202.70	18.56	307.79
SSURGO	2.37	44.61	242.23	19.11	308.32
Whole Field	0.49	74.57	223.69	11.15	309.90
Large Grid	2.29	78.55	222.92	19.87	323.63
True Deep EC/Shallow EC	2.10	48.05	284.50	18.37	350.92
Deep EC	3.38	96.25	263.82	18.33	381.78
True Deep EC	2.93	110.26	271.57	18.90	403.66

In 2017, soil fertility samples were collected for Site 7 on the same 0.4 ha grid. Shallow EC provided lowest CSM at \$249.21 ha^{-1} and large grids (6.4 ha) had the highest at \$403.66 ha^{-1}(Table 13). When sample costs were plotted against the CSM's for each grid size, the EOGSS for this site in 2017 was calculated to be 1.26 ha. When 2017 and 2018 site years are compared, both the sub-optimal pH and nutrient deficiency cost decreased from 2017 to 2018. Average soil test nutrient levels decreased by 11% for phosphorus, 8% for potassium, and pH increased from 6.1 to 6.3 from 2017 to 2018.The EOGSS was reduced by half from 2017 to 2018 suggesting that EOGSS is a dynamic measurement.

Table 13. Costs of sub-optimal management as a function of grid and zone delineation method for Site 7 in 2017 (sorted by CSM from lowest to highest)

Method	Sample Cost ($/ha^{-1})	Sub-optimal pH Cost ($/ha^{-1})	K2O or P2O5 Deficiency Cost ($/ha^{-1})	K2O Excess Cost ($/ha^{-1})	Total CSM ($/ha^{-1})
Shallow EC	2.83	90.34	233.66	17.42	344.25
Average EC	3.23	91.74	233.02	17.25	345.24
SSURGO	2.37	101.77	246.99	18.66	369.79
Deep EC	3.38	97.06	258.91	17.75	377.09
Small Grid	8.99	85.22	269.47	19.56	383.24
OM	3.12	93.39	273.15	18.86	388.53
Sand	3.08	86.52	288.76	19.17	397.53
Clay	2.75	99.89	283.06	18.78	404.48
True Deep EC	2.93	110.35	273.57	18.45	405.30
Elevation	3.33	141.26	244.19	19.34	408.11
Whole Field	0.49	135.55	265.74	12.30	414.08
True Deep EC/ Shallow EC	2.10	98.04	297.30	19.63	414.97
Medium Grid	3.94	129.83	282.47	18.48	434.72
Large Grid	2.29	153.96	281.82	20.90	458.97

Grid Sampling & Economically Optimum Grid Sampling Size

Grid sampling was evaluated for 1.6, 1.9, 2.4, 3.6, 4.4, 5.4, 6.4, 7.8, and 9.7 ha grids. For most sites as grid size increased so did the CSM. The exception was Site 6 that had high soil phosphorus levels and therefore did not have the same costly phosphorus deficiency as the rest of the sites. This agrees with previous research that suggests that smaller grids are needed to capture the spatial variability of phosphorus because of its random dispersion (Lawrence, 2019). Smaller grids account for field variability better than larger grids, resulting in a more adequate nutrient application, but also result in higher sampling costs. In order to determine the EOGSS, sampling costs and CSM, less sampling costs, were plotted for all sites for each grid size. The minimum sum of these curves occurs at a grid sampling size of 0.43 ha and represents the grid size that minimizes total costs, or the EOGSS (Figure 6, Figure 7). This agrees with Wollenhaupt et al. (1994) and Franzen et al. (1995) estimate that the EOGSS would be around 0.4 ha.

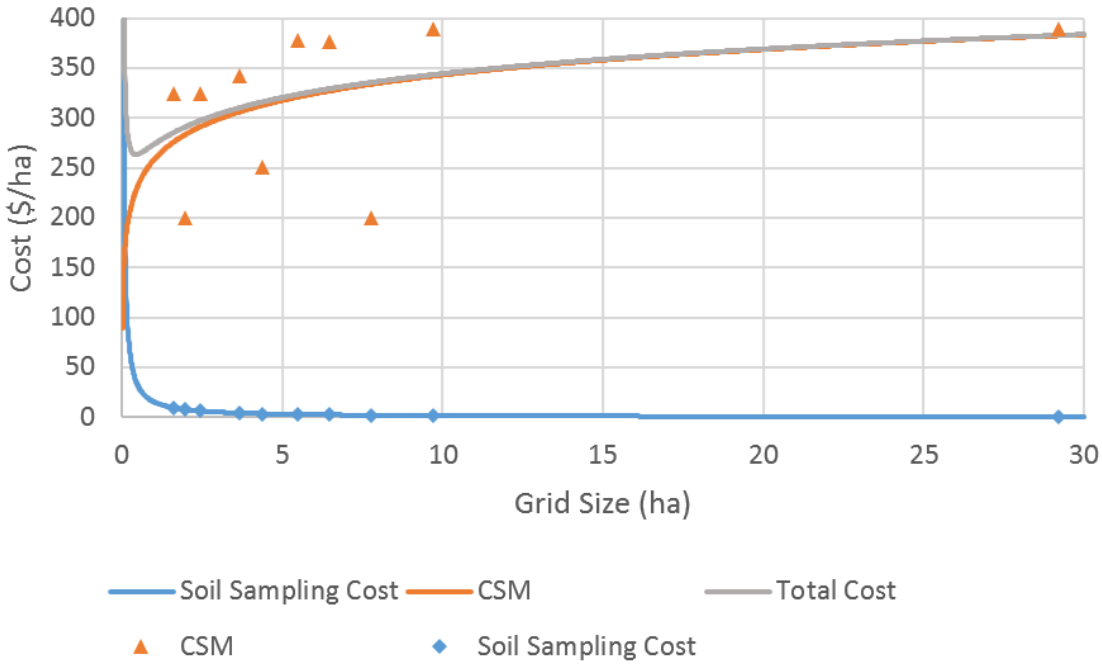

Figure 6. Overall economically optimum grid sampling size as shown by the minimum point of total cost

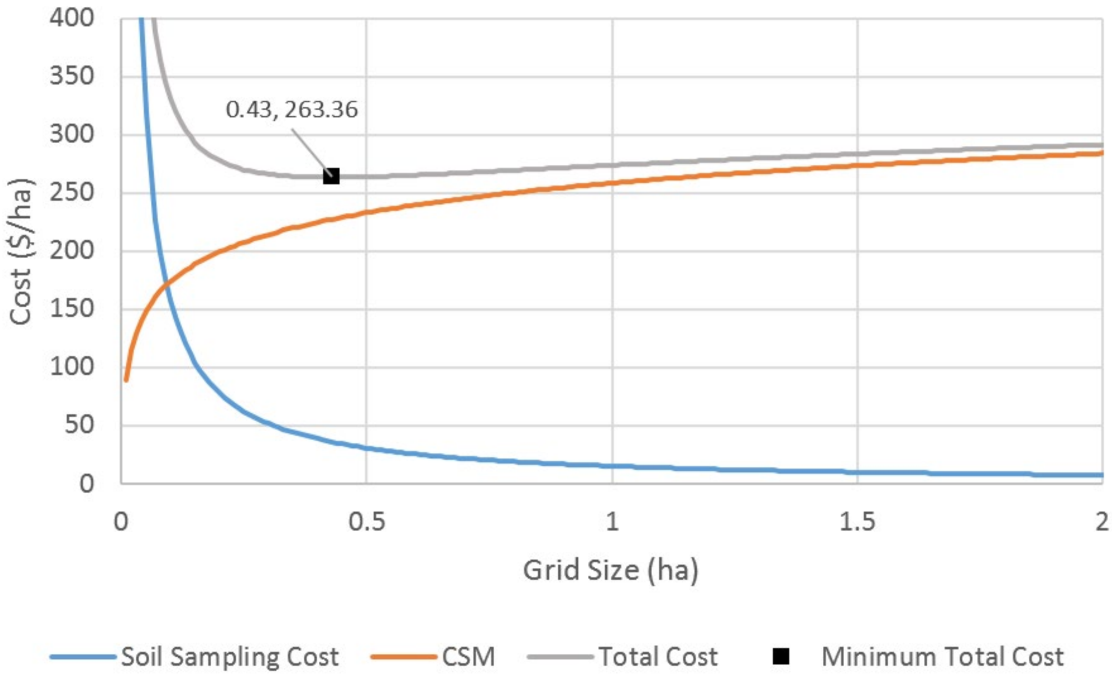

Figure 7. Close up of overall economically optimum grid sampling size as shown by the point of minimum total cost

Also, it is worth noting that the total cost, when choosing a grid size larger than the EOGSS of 0.43 ha, does not increase drastically. When a linear trend line is fitted from the EOGSS to larger grid sizes the slope of that line is 8. This means that for every ha the grid sampling size is increased by, the total cost will increase by $8. Theoretically, if the amount of variability within in a field is relatable to EOGSS, then the EOGSS could be predicted. To evaluate this, the EOGSS for each site was compared to several measures of variability, for example sand content standard deviation, in an attempt to relate field variability to the EOGSS. No good relationship was observed (Table 14). However, more work should be done to find relationships because it is hypothesized that EOGSS would be smaller on fields demonstrating higher degrees of spatial variability and larger on fields demonstrating lower degrees of spatial variability.

Table 14. Correlation of standard deviation of field attributes to EOGSS

	pH	Phosphorus	Potassium	Sand Content	Clay Content	Shallow EC	Magnesium
	SD[a]	SD[a]	SD[a]	SD[a]	SD[a]	SD[a]	SD[a]
R^2	0.025	0.000	0.088	0.029	0.032	0.030	0.122

[a] SD = standard deviation

Overall CSMs

Zone sampling seeks to divide a field into homogenous areas based on properties that are sources of variation (e.g., soil EC, soil texture). The CSMs and CSM components for each site discussed above were treated as replications for the purposes of comparing sampling methods, including both grid and zone methods. A broad range of methods appeared in the statistical grouping for lowest CSM. Sand content had the lowest numerical CSM of the zone methods evaluated at \$304.23 ha^{-1}(Table 15) but, was only statistically different from deep EC and whole field management as indicated by Student's T-test ($p<0.05$). A one-way ANOVA ($F_{100,13}=0.8102$, p=.6481) found no difference. Whole field management had the highest CSM at \$387.26 ha^{-1}but was only statistically different from sand content and small grids.

While this study does include hourly wages to collect soil samples and sample analysis cost, it does not include any opportunity cost associated with the time consumed collecting samples. Anyone spending time collecting soil samples cannot simultaneously be maintaining equipment or tending to crops in the fields. This opportunity cost can change in certain cases, for example, if an impending weather event causes the priority of a task to be increased. It is important to note that in this study the average zone size across all of the MZ methods was 10.5 ha which is much greater than the smallest grid size but good zones achieve a similar CSM. There was one statistical division for the sub-optimal pH cost indicated by Student's T test ($p<.05$) but not for a one-way ANOVA ($F_{102,13}=1.0615$, $p=0.4008$). Sand content and organic matter made up the best statistical grouping for sub-optimal pH cost. There were no statistical differences as indicated by a one-way ANOVA ($F_{98,13}=0.5832$, $p=0.8622$) or Student's T test ($p<0.05$) in the largest cost, Nutrient deficiency. Phosphorus was the limiting nutrient in most of the calculations with the exception being Site 5. Excess MOP costs did have significant differences, one-way ANOVA ($F_{93,13}=10.4976$, $p<0.0001$) and Student's T test ($p<0.05$), with whole field having the least MOP excess.

Table 15. Overall costs of sub-optimal management by management zone sorted by total cost of sub-optimal management

Method	n	Sampling ($/ha^{-1})	Sub-opt pH ($/ha^{-1})[b]	SD[a]	Nutrient Deficiency ($/ha^{-1})[b]	SD[a]	K2O Excess ($/ha^{-1})[b]	SD[a]	Total CSM ($/ha^{-1})[b]	SD[a]
Sand	9	3.08	48.44 (b)	20.67	235.30 (a)	41.96	18.05 (abcd)	0.89	304.23 (c)	54.73
Small Grid	9	8.99	57.75 (ab)	25.37	234.96 (a)	60.67	17.20 (cd)	1.96	318.89 (bc)	71.12
OM	9	3.12	54.82 (b)	22.04	263.01 (a)	30.21	18.39 (abc)	0.84	325.49 (abc)	53.35
True Deep EC/ Shallow EC	4	2.10	70.23 (ab)	23.58	239.00 (a)	68.96	18.48 (abcd)	1.55	329.81 (abc)	81.64
Shallow EC	9	2.83	58.85 (ab)	19.81	235.86 (a)	56.68	17.08 (d)	1.25	332.16 (abc)	32.73
Medium Grid	9	3.94	73.10 (ab)	46.48	240.36 (a)	73.79	17.90 (abcd)	1.36	335.30 (abc)	98.11
Average EC	9	3.23	75.05 (ab)	46.45	241.83 (a)	58.91	17.08 (d)	1.07	337.20 (abc)	75.13
Clay	9	2.75	68.96 (ab)	36.62	250.33 (a)	33.90	18.08 (abcd)	0.81	340.06 (abc)	50.87
Elevation	9	3.33	85.08 (ab)	48.84	237.39 (a)	51.06	18.78 (a)	0.76	344.07 (abc)	73.26
SSURGO	9	2.37	69.71 (ab)	31.25	256.01 (a)	17.99	18.52 (ab)	1.11	348.00 (abc)	51.33
Large Grid	9	2.29	85.61 (ab)	45.51	248.36 (a)	65.49	18.26 (abc)	1.98	354.52 (abc)	91.40
True Deep EC	4	2.93	108.24 (a)	49.75	229.11 (a)	73.73	17.02 (bcd)	2.05	357.30 (abc)	116.50
Deep EC	9	3.38	83.39 (ab)	58.12	267.41 (a)	28.52	17.45 (bcd)	0.80	375.87 (ab)	42.14
Whole Field	9	0.49	98.42 (a)	52.36	276.64 (a)	39.78	11.63 (e)	0.60	387.26 (a)	67.99

[a] SD = standard deviation

[b]Means with different letters indicate significant differences (Student's t-test, p<0.05)

Overall Zones vs. Grids vs. Uniform Management

For the purposes of comparing zone sampling, grid sampling, SSURGO, and whole field management the average CSM's were compared from all sites. Zone sampling includes all of the MZ-based methods averaged together. Small grids (<2.5 ha) resulted in the numerically lowest CSM with no significant difference from zones. Small grids decreased the CSM compared to whole field management by \$68.37 ha^{-1}. Both zone and small grid management were significantly more profitable than whole field management and the differences were sufficient to more than cover typical, premium costs associated with variable rate application.

This demonstrates, based on the assumptions of this study, that growers who do not utilize some form of PA are not achieving maximum profitability. When all zones are averaged the CSM decreased compared to whole field management by \$51.20 ha^{-1}. Additionally, whole field management, as represented in this study, is the average of all soil samples collected in a given field. In most practical applications, only one sample would be collected from a random place in the field. Therefore, the whole field management, as calculated in this study, probably resulted in a lower CSM than that for whole field management in practice.

Table 16. Grids vs zones vs uniform management

Method	n	SD[a]	Total CSM ($/ha^{-1})[b]
Small Grid	9	71.273	313.82 (b)
Medium Grid	9	98.145	332.96 (ab)
Zone	69	62.057	336.06 (b)
SURGO	9	51.251	347.11 (ab)
Large Grid	9	91.458	353.26 (ab)
Uniform	9	67.997	387.01 (a)

[a] SD = standard deviation

[b]Means with different letters indicate significant differences (Student's t-test, $p<0.05$)

Spatial Variability of Soil Nutrients

In order for a zone delineation method to accurately reflect soil phosphorus and potassium spatial variability it must account for relationships that affect a particular nutrient's ability to remain in the soil profile, in plant-available depths. Potassium, a leachable nutrient, tended to have higher soil test levels in soil, which had greater OM and lower sand content. Several zone delineation methods in this study relate to what is commonly known as "heavier ground" and therefore display a relationship to soil potassium (Figure 8).

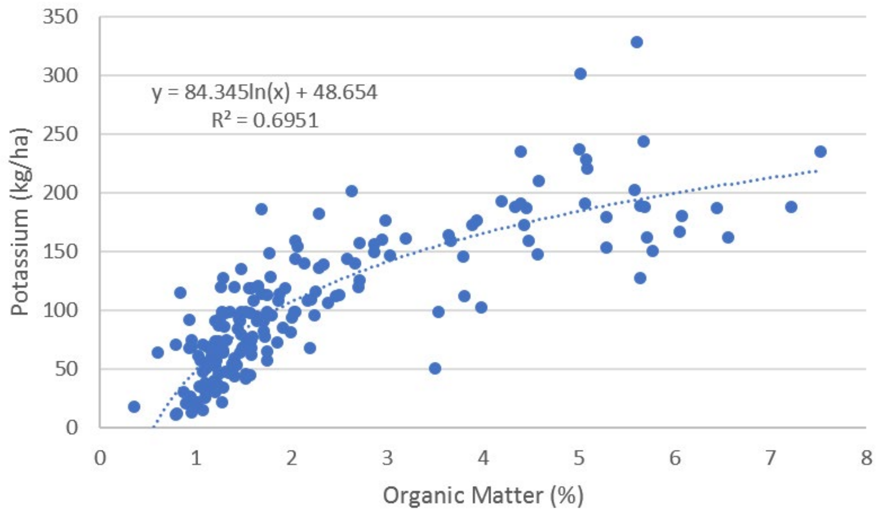

Figure 8. Spatial variability of potassium plotted against soil organic matter

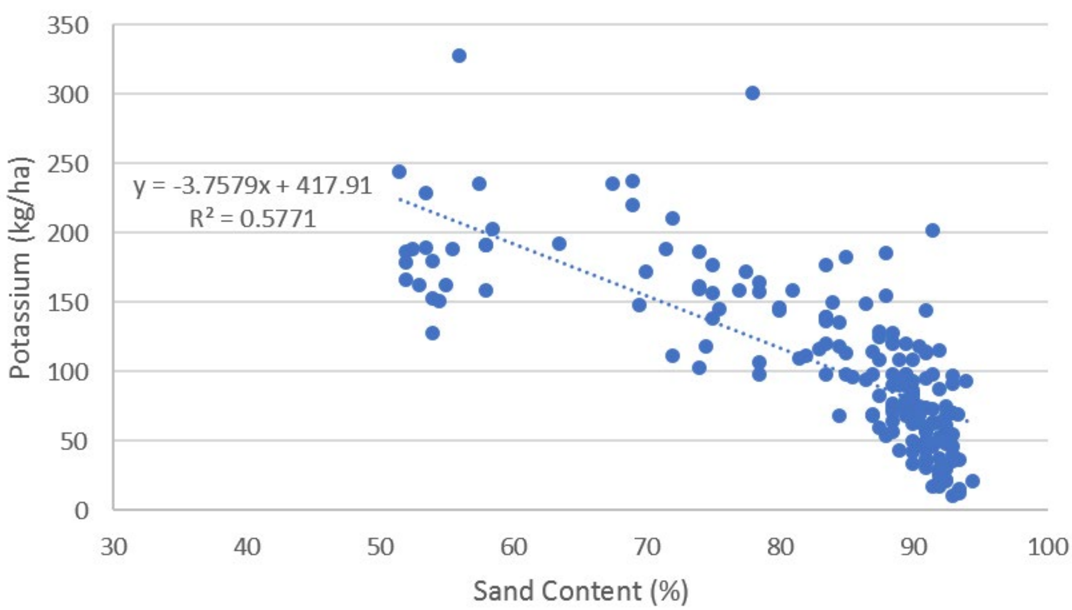

Figure 9. Spatial variability of potassium plotted against sand content

The spatial variability of soil phosphorus levels has been difficult to classify into spatial zones because phosphorous is not mobile in the soil. Previous fertilizer and manure applications greatly affect phosphorus spatial variability (Mallarino, 2005). Phophrous did not relate to any of the measured soil properties in this study. When potassium and phosphorus deficiency costs are compared, phosphorus deficiency costs are several times more than potassium as seen in Figure 10, suggesting that the prescription maps are not even close to applying an accurate rate for phosphorous.

Therefore, none of the commonly used management zone delineation methods capture the critical information that is affecting the spatial variability of soil phosphorus. Mallarino et al. (2005) recommended that dense or very small grid sampling would more accurately quantify the spatial variability of soil phosphorus levels but that zone sampling methods could be more economical if soil tests demonstrate high phosphorus levels. Whole field management looks as though it is not a bad option for phosphorus management from the data in Figure 10, however as stated above, whole field is calculated as the average of all samples collected in a given field. Therefore, in the real world, whole field management probably would not perform as well as in this study.

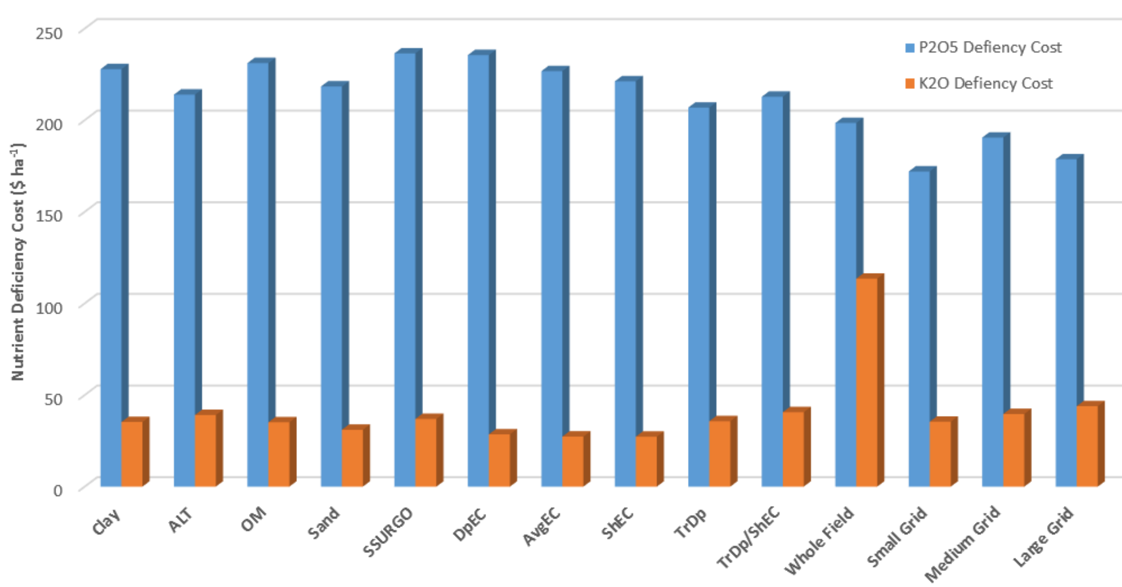

Figure 10. Nutrient deficiency costs of phosphorus & potassium

Temporal Variation of CSMs

Every year has a unique combination of rainfall, sunlight, crop rotation, temperatures, and many other factors that affect crop growth. The more a crop grows, the more nutrients are removed from the field during harvest in the form of grain or lint. Pringle et al. (2003) created the opportunity index for site specific management's ability to induce benefit a given field. They found that often the opportunity index often changed from one year to the next. In the same manner, the CSM differs from year to year for each zone delineation method, but it does appear to be relative. In the limited multi-year data that this study includes (two sites, each with two years of data) the trend appears to be that the method that generates the lowest CSM in year 1 will also do so in year 2, but not necessarily result in the same CSM. Upon further comparison of the two years of data from Site 4 several observations can be made; the same method for deriving management zones (small grids) provided the lowest CSM in both years. Also, compared to other zone delineation methods, soil EC as a whole had the lowest variation from year one to two, but deep EC did poorly in both years (Figure 10).

Consistency would be very valuable to a grower wanting to select the optimal method for deriving management zones in their operation. Fields with more soil variability inherently require smaller grids and thus more samples to capture that soil variability and vice versa. All of the CSMs were lower in 2017 than in 2018 for Site 7 (Figure 12). The EOGSS doubled from 2017 to 2018. It is unclear as to what caused the EOGSS to change this much. Average soil test phosphorus and potassium changed from 87 and 114 kg ha^{-1} to 77 and 104 kg ha^{-1} in 2017 and 2018, respectively. Also average soil pH increased from 6.1 in 2017 to 6.3 in 2018. Site 4 also shows mostly lower CSM's for 2017 (Figure 11). The EOGSS decreased slightly, around 14%, from 2017 to 2018. Average soil test phosphorus and potassium changed from 77 and 88.5 kg ha^{-1} to 60.5 and 64 kg ha^{-1} in 2017 and 2018, respectively. Average soil pH for Site 4 increased from 5.8 in 2017 to 6.2 in 2018.

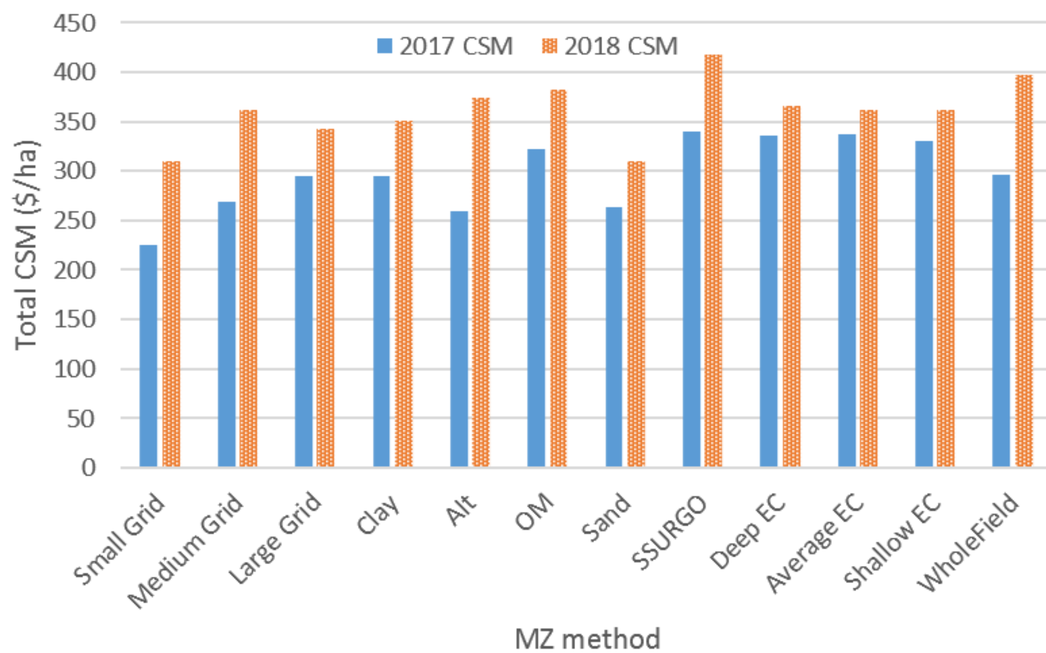

Figure 11. Two year costs of sub-optimal management for Site 4

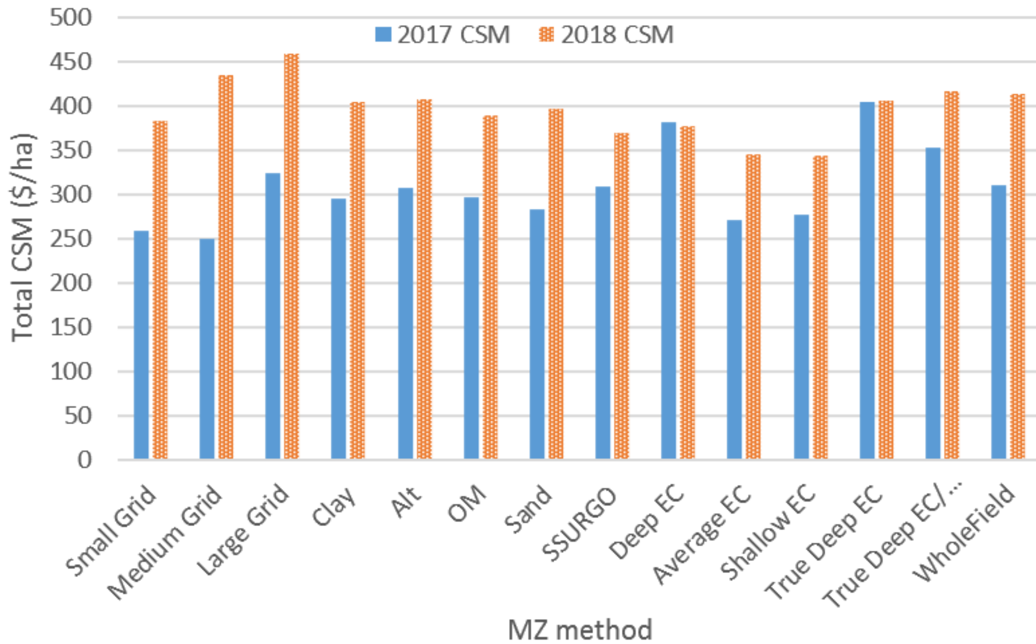

Figure 12. Two year costs of sub-optimal management or Site 7

Conclusion

Soil samples are used to determine recommendations for variable rate fertilizer application, however, limited research suggesting which sampling method has the greatest economic benefit for precision agriculture applications exists. This work describes and demonstrates a method for comparing profitability of different grid and zone development methods. In agreement with previous research, as grid sampling size was reduced the spatial variability of phosphorus and potassium was more accurately reflected in soil test results, thus resulting in a lower CSM. Small grids (>2.5 ha) provided the lowest phosphorus deficiency which agrees with previous research that suggest grids may be more suitable for phosphorus management (Lawrence, 2019; Mallarino, 2005). Based on the results of this research the EOGSS, with all fields considered, was 0.43 ha with a range of 0.33 to 1.29 ha across the nine site years and seven sites studied. This agrees with

Wollenhaupt et al. (1994) and Franzen et al. (1995) estimate that the EOGSS would be around 0.4 ha. Additionally, the EOGSS increased by $8 for each hectare of increased grid sampling size. EOGSS is likely related to regional soil variability and therefore may not represent other regions of different soils and different levels of spatial variability. The assumption that for a highly variable field EOGSS would be smaller in order to capture the increased variation. It was attempted here to correlate several measures of soil variability, such as for sand content, to the optimum grid sampling size, but no relationship was observed; more work should be done to determine if there is a simple methodology for determination of EOGSS.

Sand content was determined the best zone delineation method with regard to providing the lowest CSM. Whole field management had the highest CSM when averaged across all site years but did not come in last every time. This suggests that it is possible to do worse than whole field management if the correct MZ delineation method is not chosen.

Temporal variability may have little impact on which zone delineation method provides the lowest CSM as temporal variation was found to be generally relative. For example, from year to year, CSM values changed, but general ranking of method did not.

Soil potassium levels displayed a positive relationship with soil organic matter and a negative relationship with sand content. These relationships allowed potassium prescription maps to be more representative of soil requirements in a given zone than phosphorous prescription maps. Therefore, a higher cost was associated with phosphorous under application than that for potassium under application in most fields. Future research should evaluate the potential of using separate methods of zone delineation for potassium, phosphorous, and lime applications. In future work, historic yield data should also be evaluated as a potential method to determine soil sample management zones.

CHAPTER 4. CONCLUSIONS

Two methods were developed, described, and applied for comparison of grid versus zone management in precision agriculture applications. A scoring system was developed, which calculates a management zone scoring index (MZSI) for a given grid or zone management method; in short, the MZSI is a measure of how well a zone or grid development method maximizes differences between zones and how well it minimizes differences within zones. Differences, in this study were based on historical yield data. A methodology for determining and comparing profitability between grid and zone development methodologies was also developed and applied to demonstrate its utility in comparing the cost of suboptimal management (CSM) between methods.

The development and implementation of the MZSI system provided several insights into zone management development systems. First, same-crop composite yield maps produced the highest score of any zone delineation method. This demonstrates, at least from a quantitative view, that composite yield maps capture the most variability of the tested MZs. This is logical because composite maps have more data and can account somewhat for temporal variability because they span multiple years. Second, because it takes a long period of time to build a same-crop composite yield map due to crop rotations, it may be tempting to create a yield map from one year of yield data and apply it to another crop the following year. When using only one year of yield data, same-crop data consistently scored higher than different-crop data, which ranked in the bottom half of all methods. Corn and cotton data were evaluated here; considering these two crops, it is not recommended to use one year of yield data from a given crop to create MZs to be used for the other crop. Third, irrigated data is less variable than dryland data. This is believed to result from less dependence on rainfall for optimum growth. This also results in a greater ability to find significant differences in MZSI across multiple zone development methodologies. Fourth, elevation produced the lowest score in almost every comparison and therefore it may not be suitable to use elevation as a zone delineation method, when the goal in zone management is in creating relatively homogenous yield zones. Finally, how the data is numerically divided into zones is important. Zones divided using ½ standard deviation divisions produced a higher MZSI than 4 equal divisions, but it was not statistically significant. Therefore, four equal divisions may be suitable for most precision agriculture operations, at a lesser cost, since it generally involves three less zones than ½ standard deviation divisions.

When the costs associated with several MZ and grid methods were analyzed by the development and implementation of the CSM methodology presented here, several conclusions were made. First, as grids decrease in size they more accurately capture field variability but sampling cost increases exponentially. Second, the EOGSS was determined for the sites in this study, which are within southeastern coastal plains soils, to be 0.43 ha. This is in agreement with Wollenhaupt et al. (1994) and Franzen et al. (1995) estimate that the EOGSS would be around 0.4 ha. This EOGSS is likely related in large to regional soil variability and therefore may not represent other regions of different soils. Third, EOGSS and field variability did not correlate with measures of in-field variability assessed here; if relationships could be found, prediction or estimation of EOGSS for a given field could be accomplished. The ability to predict the EOGSS would save both time and money in the sampling process would be an invaluable tool for consultants and farmers who utilize grid sampling. Most grid sizes employed in variable rate nutrient management have no scientific basis for why one size was selected over another. Fourth, sand content provided the lowest CSM followed closely by small grids (>2.5 ha) but reduced the sampling cost by 57%. Fifth, temporal variability was found to be somewhat relative in relation to the CSM. Generally, the ranking of grid and zone methods was similar in both years of this study's limited multiyear data. Sixth, soil potassium levels correlated well with multiple datasets used to create MZs. However, soil phosphorus levels did not correlate to any MZ delineation method explored here, which helps to explain why it represented the bulk of the costs associated with sub-optimal fertilizer placement.

In future work, the CSM methodology should be applied to MZs generated from yield data, especially same-crop composite yield maps. Additionally, future work should evaluate the potential of using separate methods of zone delineation for potassium, phosphorous, and lime applications. Within this, the MZSI methodology could be applied to evaluate and compare zone and grid methodologies for grouping the field into pH management zones; in this study differences considered were on the basis of yield, but the same procedures could be applied where the differences considered are on the basis of pH or lime recommendation. Further attention should be given to evaluate the relationship of the EOGSS to a measure of field variability as this would be an invaluable tool for consultants and farmers who utilize grid sampling. Alternatively, if regional measures of EOGSS were developed, tested, and validated, practitioners of grid sampling would at least have some beginning basis for establishing the most profitable grid size for their areas.

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